ASSESSMENT OF ENVIRONMENTAL AND MANAGEMENT FACTORS IMPACTING THE PHOSPHORUS LOADING IN AN AGRICULTURAL WATERSHED

A Dissertation

by

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ABSTRACT

Runoff with high phosphorus (P) concentrations from agricultural, industrial and domestic land uses is contributing to detrimental environmental changes throughout the entire ecosystem. To examine this phenomenon, three studies examining P were conducted. The first study was devoted to water and P budgets of a large agricultural basin located in South Florida (Everglades Agricultural Area, EAA). Water and P budgets were computed from 2005 to 2012. The annual surface outflow P loading from the EAA averaged 157.2 mtons originating from Lake Okeechobee (16.4 mtons, 10.4%), farms (131.0 mtons, 83.4%), and surrounding basins (9.8 mtons, 6.2%) after attenuation. Farms, urban areas, and the adjacent basin contributed 186.1, 15.6, and 3.8 mtons/yr to the canals, respectively. The average annual soil P retention was estimated at 412.5 mtons. Moreover, results indicated that the canals acted as a P sink storing 64.8 mtons/yr. To assess the P loading impact of farm drainage on the canals and on the outflow, dimensionless impact factors were developed.

The second study developed a new methodology using multi-temporal Normalized Difference Vegetation Index (NDVI) data derived from Landsat images to map sugarcane and its rotation in the EAA. A cloud and cloud shadow removal procedure that applies to patchy clouds over agricultural fields was developed to facilitate crop mapping. Three classes related to sugarcane planting and crop rotation (sugarcane, mixed crops, and fallow) were generated using a Decision Tree Analysis (DTA) algorithm. The DTA model can produce

up-to-date agricultural maps for the purposes of environmental management and therefore circumvents issues related to limited field data.

The third study combined the results of the first two studies to identify environmental and management controls of P loading in the EAA from 2010 to 2014. Multivariate analyses were conducted using the following environmental variables for 38 farms in the S5A sub-basin: (1) total P load per unit area (2) best management practices (BMP) types (3) land cover (4) soil type (5) current and antecedent rainfall (6) distance of farms from sub-basin outlet (7) farm perimeter and (8) seasonality. Current and antecedent rainfall contributed significantly to the release of P load in the farm runoff. P load was also influenced by the percentage of mixed vegetation land cover, the interaction of seasonality and BMP type, farm perimeter and distance of farms from sub-basin outlet.

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NOMENCLATURE

EAA	Everglades Agricultural Area
mton	metric tone
P	Phosphorus
EvPA	Everglades Protection Area
BMP	Best Management Practices
STA	Stormwater Treatment Area
NDVI	Normalized Difference Vegetation Index
ppb	parts per billion
hm^3	cubic hectometer

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1. INTRODUCTION

Phosphorus (P) is a vital element and an essential nutrient and energy carrier for all life forms (Pierzynski et al., 2005, Sharpley et al., 2001) yet the main source of P, (phosphate rock) is a non-renewable resource and high quality reserves are becoming increasingly scarce (Cordell, 2010, Hammond et al., 2004). P is often a limiting nutrient in freshwater environments and its availability may govern algal growth or primary production (Elser, 2012, Sterner, 2008). High P concentrations in runoff from agricultural, industrial and domestic sources is contributing to significant detrimental environmental changes throughout entire ecosystems and is causing risks to human health and well-being (Sklar et al., 2005). In the context of the Florida Everglades P concentrations higher than 10 ppb cause overgrowth of algae and eutrophication (Sklar et al., 2005). Enrichment of P in aquatic ecosystems from agricultural runoff is often leading to algal blooms and to the formation of hypoxic zones caused by the death and decomposition of aquatic vegetation (Sharpley et al., 2000, Noe et al., 2001).

High P concentrations in farm runoff generally originate from the application of fertilizers in excess of plant needs leading to accumulation and eventual saturation of available P in the soil and to the diffuse loss of P to surface waters (Carpenter, 2005). This scenario is called legacy P (Sharpley et al., 2013). The addition of high loads of P to these aquatic environments can have significant ecological consequences such as eutrophication (Sharpley et al., 2001, Tilman et al., 2001). Even a relatively small P load discharged to a water-body may cause its eutrophication given the sensitivity of aquatic autotrophs to P enrichment (Smil, 2000). Eutrophication is the over enrichment of natural waters by nutrients such as P has emerged as one of the leading causes of water quality impairment and deterioration with the two most acute symptoms of hypoxia and extensive algal blooms destroying aquatic life in affected areas and posing threat to human health (World Resources Institute, 2010). Many lakes in the United States are eutrophic, including Lake Erie (Michalak et al., 2013) and Lake Okeechobee (Havens et al., 2001). Famous international examples are Lake Victoria in Malawi and Lake Taihu in China (Guildford and Hecky, 2000).

Increased agricultural production around the world has increased the amount of P discharged to rivers, lakes and oceans (Sharpley and Rekolainen, 1997) .In developing countries agricultural production has increased by 3.4% annually over the last two decades (Angelsen, 2010) .Intensive agriculture in the Brazilian Amazon grew by more than 3.3 million hectares during 2001-2004 (Morton et al., 2006). During the last 100 years, land use in southern Florida has changed substantially, shifting from a natural, wild landscape to intensive farming (Solecki and Walker, 2001). In Europe, agricultural discharge of P to freshwater exceeded 0.1 kg P ha^{-1} yr^{-1} across much of the continent, and reached levels in excess of 1.0 kg P ha^{-1} yr^{-1} in hotspots, affecting plant biodiversity in natural ecosystems and upsetting the biological balance (Synthesis, 2010).

The Everglades Agricultural Area (EAA) basin in south Florida presents a good example of the impact of P load on the unique wetland ecosystem called the Everglades where eutrophic conditions result in environmental degradation which pose a serious health hazard to humans, plants and animals. The vast decadal growth in sugarcane fields in southern Florida led to severe environmental changes that have not been limited to marked reductions in wildlife populations (Noe et al., 2001).

Once an aquatic ecosystem is degraded, remedial strategies are often expensive and the recovery is slow as it can take many years to reverse the damages (Carpenter, 2005). Restoration of an ecosystem requires substantial soil management and implementation of BMPs (Carpenter, 2005). Oehl et al. (2002) compared the impacts of implementing innovative farming practices to conventional farming practices on the accumulation of total and available P in a cropped soil. The innovative farming practices was a balanced P budget at the farm level and the conventional farming practices involved P fertilization at rates exceeding the amount of P removed by crops. Their analysis showed substantially higher P concentrations in the topsoil from farms implementing conventional practices for 21 years compared to farms implementing innovative practices.

The EAA is a large and mainly agricultural watershed draining into the Everglades Protection Area (EvPA); a major freshwater and historically P-limited wetland system. High P concentrations in the EvPA originating from the EAA have been the cause of imbalances in the flora and fauna of natural populations (Childers et al., 2003). While some BMPs have been implemented in the EAA to control P at the source and six Stormwater Treatment Areas (STAs) have been built and are currently operated to remove P from the EAA runoff before it flows into the EvPA, the outflow P concentration from STAs to the EvPA have exceeded the Florida Department of Environmental Protection recommended long term threshold of 10 ppb (Sklar et al., 2005). The mean outflow P concentration in water discharged from all STAs during the period of record of 1994-2012 is 37 ppb (SFWMD, 2013). Given the sensitivity of the native biological population to even a small change in P concentration (McCormick and Stevenson, 2002), additional water quality improvement measures are necessary. As further expansions of STAs are extremely costly, they should be considered as an additional measure when the effect of preventative measures (BMPs) is fully exhausted.

Different on-farm conservation programs have been implemented in agricultural basins but were not successful in improving water quality as predicted by watershed scientists (Sharpley et al., 2013, Jarvie et al., 2013). Examples include the Chesapeake Bay watershed (Reckhow et al., 2011), Mississippi River basin (USEPA, 2011), Florida's inland waters (USEPA, 2011) and the Lake Erie basin (Sharpley et al., 2011), where BMPs to reduce P loading from agriculture were implemented to minimize water quality degradation due to eutrophication (Sharpley et al., 2013). In the EAA basin, numerous factors have been suggested as affecting P load from farms such as P concentration in irrigation water, cropping system, farm water management and site-specific variables such as farm size, soil type and land use practices (Daroub et al., 2009, Grunwald et al., 2009, Lang et al., 2010, Izuno et al., 1995). Due to limitations associated with monitoring, these studies were conducted at few specific research farms and did not account for heterogeneity of farms in the basin. Despite these research findings, our understanding of how farms with different environmental, management, land use and site specific variables and BMP types affect P loads is limited. Furthermore, in a typical large agricultural basin with a dominant sugarcane crop, the main P loading sources and sinks and the impacts of farming on the accumulation of legacy P stored in the soils and canal sediments are not known.

To assess the variables impacting the P loadings from farms or the legacy P stored in soils, land use has to be determined with great accuracy. Moreover, considering the environmental impact of agriculture, researchers and decision makers in environmental management need tools that can provide trustworthy and reproducible annual information on type of crops and their rotations and the planted dates and areas. This type of information is generally well guarded by farmers and, even if shared, data is not always accurate and the system can become cumbersome if covering a large area. Remote sensing can overcome shortages of field survey data collection while providing continuous and consistent land use information. It can also be used to verify information provided by farmers.

The objective of this research was to assess complex environmental and management factors impacting the P loadings from farms and develop necessary tools for tracking environmental performance across an agricultural basin, identify critical areas and target those in need of additional BMPs.

2. PHOSPHORUS AND WATER BUDGETS IN AN AGRICULTURAL BASIN*

2.1 Introduction

At global and regional scales, the consequences of P pollution from diffuse sources are well known (Seitzinger et al., 2005, Quynh et al., 2005). However, there is always a need for site-specific nutrient budgets at a basin scale to assess the nutrient loading rates as an indicator of sustainable agriculture practices (Borbor-Cordova et al., 2006). Nutrient budgets are an important source of information to water resource managers mainly emphasizing the need for intermediate storage rather than focusing on downstream fluxes (Pionke et al., 2000, Walling and Collins, 2008, Sigua and Tweedale, 2003). In this context, this study is targeting the intensively managed Everglades as one example of a P impacted ecosystem from anthropogenic sources. Since efforts are underway to restore this unique ecosystem (Sklar et al., 2005) and considering the critical location and multifaceted importance of the EAA, a rigorous P balance over this area is important. This work aims at providing such an input.

This work offers a detailed water and P budgets conducted for the EAA farms and canals, based on data from 8 water years (WY 2005 – 2012), to identify the main P loading sources and also the impacts of farming on building-up the amount of legacy P stored in the soils and in the canal sediments. This would provide essential guidance for managing

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nutrients in the EAA runoff before they reach the STAs and EvPA. In 1994, Abtew et al.(1994) presented a detailed EAA water budget analysis but did not investigate the P budget. A few other papers reported P budget analysis of specific farms,(CH2M-HILL, 1978, Izuno et al., 1995) but no budget analysis was attempted at the large EAA scale. Moreover, impact factors were developed in the present paper assessing the degree of impact of the farms P loadings onto the STAs, while linking the farm P load, variances in farm areas and in Lake Okeechobee irrigation water P concentration. These factors are a simple novel tool that could be used to identify and select critical areas in a sub watershed and targeting those with specific innovative BMP.

Although this study was directed specifically at quantifying P loadings and implementing impact factors in a specific agricultural watershed, results have important implications for many other basins in similar landscapes facing similar nutrient problems. In addition, the methodology provided below has broad applicability for the assessment of non-point source nutrient loadings and would provide essential guidance for managing nutrients in runoff before reaching sensitive ecosystems.

2.2 Materials and Methods

2.2.1 Study Area

The EAA basin consists of six drainage sub-basins (S-2, S-3, S-5A, S-6, S-7 and S-8) and four urban areas. To not mix urban and agricultural land uses, the study area only included the six agricultural drainage sub-basins grouped into four hydrologic sub-basins, namely S-5A, S-2/S-6 (sub-basins S-2 and S-6), S-2/S-7 (sub-basins S-2 and S-7) and S-3/S-8 (sub-basins S-3 and S-8). The area of the four studied sub-basins in hectares is

48,324, 51,113, 44,920 and 46,841 for S-5A, S-2/S-6, S-2/S-7 and S-3/S-8 sub-basins, respectively. The EAA is further subdivided into hydraulic drainage areas or farms with a unique farm identification (SFWMD, 2012). Figure 1 shows the study area, the investigated sub-basins and the primary canals.

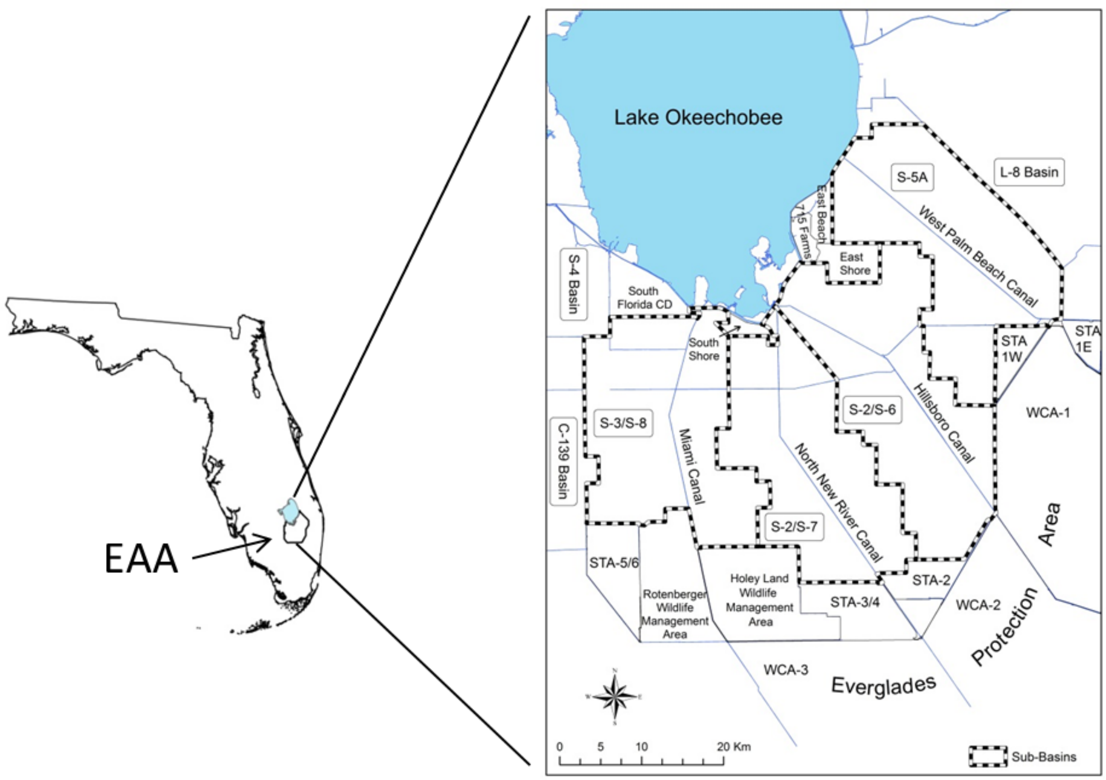


Figure 1- Map showing the location of the EAA, the EvPA, as well as the Stormwater Treatment Areas (STAs) 1E, 1W, 2, 3/4, 5 and 6. Four main canals are crossing the EAA, namely the West Palm Beach (WPB), Hillsboro (HBR), North New River (NNR) and Miami (MM) canals. The study area includes S-5A, S-2/S-6, S-2/S-7 and S-3/S-8 sub-basins. The four urban areas are South Shore, 715 Farms and East Shore, East Beach, and South Florida Conservancy District.

The EAA is characterized by a flat topography with drained rich organic soil predominately histosols, underlain by relatively low-permeability limestone formation of Fort Thompson (Richardson, 2008). According to the land use information from the South Florida Water Management District (SFWMD), the land use classification in the study area (of 191,198 ha) is mainly sugarcane and vegetable fields (93%), barren land (2.3%), urban (2.3%), waterbodies including wetlands and canals (1.7%), and improved pastures (0.4%).

The irrigation / drainage system in the EAA watershed is a complex network of primary and secondary canals, and hydraulic structures such as pump stations and spillways (Abtew and Khanal, 1994) . Surface water is impounded by a system of levees and inflows and outflows occur through control structures located on the primary canals. The primary control systems are operated and maintained by the SFWMD(2011). The primary canals are Miami (MM) canal in S-3/S-8 sub-basin, North New River (NNR) canal in S-2/S-7 sub-basin, Hillsboro (HBR) canal in S-2/S-6 sub-basin and West Palm Beach (WPB) canal in S-5A sub-basin, running from north to south and southeast. A schematic model of the water control structures for WYs 2005-2012 is shown in Figure 2 and Figure 3.

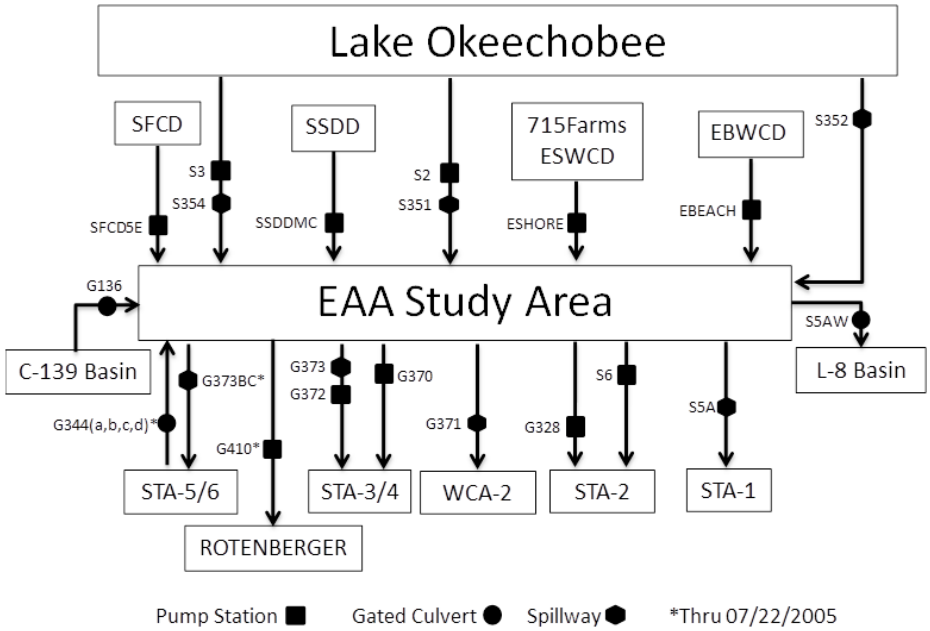


Figure 2- EAA flow control structures for WYs 2006-2012. WCA stands for Water Conservation Area, part of the EvPA. SSDD, ESWCD, EBWCD and SFCD represent the South Shore Drainage District, the East Shore Water Control District, the East Beach Water Control District, and the South Florida Conservancy District, respectively.

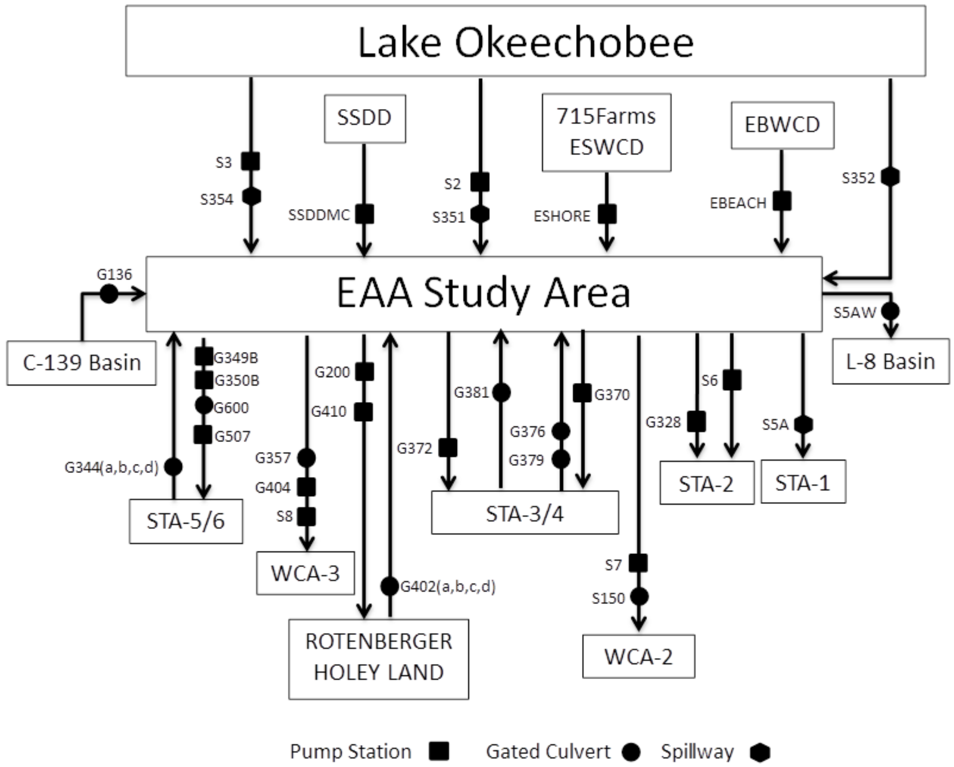


Figure 3- EAA flow control structures for WY 2005.

At the farm level, water is managed by controlling the water table in such a way that during the dry season (November through April), irrigation water is sourced from Lake Okeechobee by gravity and during the wet season (May through October) excess water (drainage or runoff) is drained from the farms to the primary canals leading to the STAs. In order to retain the surface flow and create drainage divides, each farm is dissected by drainage canals and therefore there is no overland flow. Farm pump stations (private pumps), culverts and field ditches operated by the farmers are used for water drainage and irrigation at the farm level (Abtew and Khanal, 1994). Maintaining the water level elevation is an important hydrological factor and is one of the BMPs implemented to control the farm P load in the runoff (Daroub et al., 2007). Water level management is also a key factor to optimize the agricultural yield and to control the soil subsidence and the soil oxidation rate (Abtew and Khanal, 1994, Reddy and DeLaune, 2008).

2.2.2 Data Collection

WYs 2005-2012 were selected for this study since the hydraulic control structures and water management were different before 2005. A water year (WY) is defined as the twelve-month period from May to April. The monthly rainfall data was obtained from the South Florida Environmental Reports (http://www.sfwmd.gov/portal/page/portal/pg_grp_sfwmd_sfer/). The mean historical (1973 - 2012) annual rainfall for the EAA was 122.2 cm. Monthly evapotranspiration (ET) rates with a spatial resolution of 1 km^2 were obtained from the MOD16 global ET datasets following the methodology developed by Mu et al.(2011). To provide an accurate estimate of P deposition and overcome the concern regarding differences in sampling, data for P deposition from different studies were pooled and compared. The most recent dynamic model for STAs assumed a P concentration in rainfall at 10 $\mu g\ L^{-1}$ (Wang et al., 2012) and the dry P deposition rate at 20 $mg\ m^{-2}\ yr^{-1}$(Walker Jr and Kadlec, 2011, Knight and Keller, 2004) values consistent with P deposition estimates from bulk collectors throughout Florida,(Hendry et al., 1981) from the EvPA,(Walker Jr, 1993) and from average values reported by Ahn,(1999) Ahn et al.,(2001) and Chimney et al.(1999).

Flow discharge rates and TP concentrations monitored data (from composite samples) were obtained from the SFWMD online database (http://www.sfwmd.gov/dbhydro). All measurements used in this study followed the State of Florida quality assurance and quality control requirements. P concentration minimum detection limit was 2 µg L^{-1}. Daily P loading from each structure was calculated as the product of the daily mean P concentration (obtained after a linear interpolation) (SFWMD, 2010) and the daily water discharge. Monthly and annual P loading and water flow were calculated as the sum of daily values. The control structures used for the P load calculations are listed in Table 1.

Table 1- Site names, structures and period of record used for the P load calculations.

Sub -Basin	Site Name	Flow Data Sources				Water Quality Station
		DBKEY	Recorder	Type	Period of Record	
S-5A	EBPS3	LX274	PREF	Pump	7/1/2001-4/30/2013	EBEACH
	S5A+S5AW	15031	PREF	Pump	7/1/1999-4/30/2013	S5A
	HGS5X	15068	PREF	Spillway	1/1/1963-4/30/2013	S352
S-2/S-6	S6	15034	PREF	Pump	1/1/1963-4/30/2013	S6
	G328	J0718	PREF	Pump	4/1/2000-4/30/2013	G328
	S2	15021	PREF	Pump	1/1/1963-4/30/2013	S2
	ESPS	LX273	PREF	Pump	12/20/2001-4/30/2012	ESHORE 2

Table 1- Continued.

Sub -Basin	Site Name	Flow Data Sources				Water Quality Station
		DBKEY	Recorder	Type	Period of Record	
S-2/S-7	G370	TA438	PREF	Pump	10/1/2003-4/30/2013	G370
	S7	15037	PREF	Culvert	01/1/1963-3/31/2013	S7
	S150	15041	PREF	Culvert	01/1/1969-3/31/2013	S150
	G376B G376E	TA582 TA583	PREF	Culvert	10/1/2003-3/31/2013	G376B G376E
	G379B G379D	TA584 TA585	PREF	Culvert	10/1/2003-3/31/2013	G379B G379D
	G371	TS261	PREF	Spillway	2/1/2006-4/30/2013	G371
S-3/S-8	S3	15018	PREF	Pump	1/1/1963-4/30/2013	S3
	G410	LX270	PREF	Pump	7/17/2001-3/31/2013	G410
	G372	TA437	PREF	Pump	10/1/2003-4/30/2013	G372
	G373	TS260	PREF	Spillway	2/15/2006-4/30/2013	G373
	G200A	15736	PREF	Pump	1/1/1965-6/30/2008	G2001
	S8	15040	PREF	Pump	1/1/1963-4/30/2013	S8
	G404	LX269	PREF	Pump	5/6/2000-12/31/2012	G404
	G357	LX263	PREF	Culvert	1/3/2001-12/31/2012	G357
	G600	GG955	PREF	Culvert	3/6/1997-7/30/2010	G600
	G349B	JA353	PREF	Pump	10/1/1999-3/31/2013	G349B
	G350B	JA352	PREF	Pump	10/1/1999-3/31/2013	G350B
	G507	SJ382	PREF	Pump	2/24/2001-12/31/2012	G507
	G373BC	-	-	-	-	-
	G381B G381E	TA586 TA587	PREF	Culvert	10/1/2003-3/31/2013	G381B G381E

Table 1- Continued.

Sub -Basin	Site Name	Flow Data Sources				Water Quality Station
		DBKEY	Recorder	Type	Period of Record	
S-3/S-8	G402A G402B G402C G344A G344B G344C G344D	LX264 LX265 LX266 J0719 J0720 J0721 J0722	PREF	Culvert	10/1/1999-3/31/2013	G402A G402B G402C G344A G344B G344C G344D
	SSDDMC	TA459	PREF	Pump	6/1/2004-4/30/2012	SSDDMC
	G136	15195	PREF	Culvert	10/1/1978-4/30/2012	G136
	SFCD5E_P	TR998	PREF	Pump	12/17/2004-6/30/2012	SFCD5E

At the farm level, water quality and discharge data from all the private pump stations operated by farmers in the study area were used to calculate P loadings from farm runoff. The inventory of these private pumps was based on the Everglades Works of the District Permit for each farm and the corresponding data obtained from the SFWMD.

The import and export coefficients of each land use were determined based on the surveys performed by the SFWMD(2010) in south Lake Okeechobee region. The net P import rate (P mass in fertilization minus harvesting - mtons ha^{-1} yr^{-1}) for each land use was estimated as the sum of P mass in materials imported (fertilizers) minus the mass of P in materials exported (harvest). The fertilization rate for sugarcane was averaged at 19.5 kg P ha^{-1} yr^{-1} based on the typical five-year cycle of plant-cane, first ratoon crop, second ratoon crop, third ratoon crop and fallow with vegetables (SFWMD, 2010). The export rate was estimated at 16.2 kg P ha^{-1} yr^{-1}, therefore the net P import rate would be around

3.3 kg P ha^{-1} yr^{-1}. The quantities used by SFWMD(2010) are within the range of other studies. Snyder(1994) reported that since EAA soils are high in organic matter but low in P, the cropping system utilizes a high P fertilizer input ranging from 15 to 150 kg P ha^{-1} yr^{-1} for sugarcane and vegetable crops (Castillo and Wright, 2008, Hochmuth et al., 1996, Gilbert and Rice, 2006) .Glaze et al.(2000) also reported 24 kg P ha^{-1} yr^{-1} as an often-recommended sugarcane fertilizer application rate.

2.2.3 Mass Balance Components

Water and P budgets were assessed for the four sub-basins using the mass balance model presented by Abtew et al.(1994) and Boggess et al.(1995). The storage components of the P budget model consisted of soil P retention and P assimilation in the primary canals. The flow components of the water budget model consisted of inflows and outflows through control structures, drainage and irrigation.

Drainage (runoff) is defined as the quantity of excess rainfall (neither retained on the land surface nor infiltrated into the soil) and amount of water discharged by farmers mainly during the wet season to lower the water table elevation according to their needs (Abtew and Khanal, 1994) .The drainage water amount was calculated for each sub-basin by summing up the daily amounts of flow being discharged from each farm in the sub-basin to the corresponding primary canal (Lang et al., 2010). Irrigation water is defined as the quantity of water supply needed (mainly during the dry season) for crop irrigation or to raise the water table elevation (Abtew and Khanal, 1994). Irrigation water cannot be directly measured since it is withdrawn by gravity; it is rather estimated as the Lake Okeechobee inflow minus flow-through of the corresponding primary canal in the sub-basin (SFWMD, 1992). Since the urban areas and C-139 basin are mainly constituted of farms, their inflows to the EAA were not considered as part of the EAA irrigation water. Flow-through is the quantity of flow released from Lake Okeechobee to the south through the primary canals for regulatory purposes and to address water demands downstream (flood control, water supply, or to maintain canal and EvPA stages) (Abtew and Khanal, 1994). It is generally considered that this flow-through water passes through the basin and has limited interaction with the surrounding agricultural lands(SWET, 2010). The flow-through quantity was calculated using a set of conditional formulae established by the Rule 40E-63(SFWMD, 2001). Finally, the vertical seepage loss was assumed negligible, since the underlying layer has relatively low permeability(Richardson, 2008) and the horizontal seepage was also assumed negligible for model simplification (Abtew and Khanal, 1994).

2.2.4 Water and Phosphorus Budget Models

Based on the mass balance model presented in equation 1, the basin water and P budgets were stated as a series of mass balance equations. Equations 2, 3 and 4 were used to develop the water budget for each sub-basin.

$$\Delta Storage = \sum Inflows - \sum Outflows \quad (1)$$

$$\Delta S_b = \sum I_b - \sum O_b \quad (2)$$

$$I_b = I_{Inflow} + I_{Precip_b} \quad (3)$$

$$O_b = O_{Outflow} + O_{ET_b} \quad (4)$$

Where ΔS_b is the change in water storage in the sub-basin, I_b is the total inflow into the sub-basin, O_b is the total outflow from the sub-basin, I_{Inflow} is the surface inflow from lake Okeechobee, urban areas and C-139 basin through the primary control structures, $O_{Outflow}$ is the surface outflow to Lake Okeechobee (backflow) and from the net outflow water through the primary downstream control structures, I_{precip_b} is the rainfall over the sub-basin and O_{ET_b} is the ET from the sub-basin. All terms are expressed in cubic hectometer per year (hm^3 yr^{-1}).

Equations 5, 6 and 7 were used to develop the water budget for each canal.

$$\Delta S_c = \sum I_c - \sum O_c \tag{5}$$

$$I_c = I_{Inflow} + I_{Drainage} + I_{Precip_C} \tag{6}$$

$$O_c = O_{Outflow} + O_{Irrigation} + O_{ET_c} \tag{7}$$

Where ΔS_c is the change in water storage in the canals, I_c is the total inflow into the canals, O_c is the total outflow from the canals, I_{precip_C} is the rainfall over the canals, O_{ET_c} is the ET from the canals, $I_{Drainage}$ is the drainage discharges from the farms into the canals, $O_{Irrigation}$ is the irrigation demand from the canals to the farms. All terms are expressed in cubic hectometer per year (hm^3 yr^{-1}).

Equations 8, 9 and 10 were used to develop the P budget for each sub-basin.

$$\Delta \boldsymbol{S_b} = \sum \boldsymbol{I_b} - \sum \boldsymbol{O_b} \tag{8}$$

$$\boldsymbol{I_b} = \boldsymbol{I_{Inflow}} + \boldsymbol{I_{Atm_b}} + \boldsymbol{I_{net\ import}} \tag{9}$$

$$\boldsymbol{O_b} = \boldsymbol{O_{outflow}} \tag{10}$$

Where $\Delta \boldsymbol{S_b}$ is the sub-basin P retention determined by the balance between inputs and outputs, $\boldsymbol{I_b}$ is the total P load flowing into the sub-basin, $\boldsymbol{O_b}$ is the total P load flowing from the sub-basin, $\boldsymbol{I_{Inflow}}$ is the P load flowing from lake Okeechobee, urban areas and

C-139 basin through the primary control structures, $\boldsymbol{O_{Outflow}}$ is the P load discharged from the canals (backflow) to Lake Okeechobee and from the net P load through the primary downstream control structures, $\boldsymbol{I_{Atm_b}}$ is the amount of P from atmospheric deposition over the sub-basin and $\boldsymbol{I_{net-import}}$ is the net P import. All terms are expressed in metric ton per year (mtons yr^{-1}).

Equations 11, 12 and 13 were used to develop the P budget for each canal.

$$\Delta \boldsymbol{S_c} = \sum \boldsymbol{I_c} - \sum \boldsymbol{O_c} \tag{11}$$

$$\boldsymbol{I_c} = \boldsymbol{I_{Inflow}} + \boldsymbol{I_{Drainage}} + \boldsymbol{I_{Atm_C}} \tag{12}$$

$$\boldsymbol{O_c} = \boldsymbol{O_{Outflow}} + \boldsymbol{O_{Irrigation}} \tag{13}$$

$$\Delta \boldsymbol{S_b} = \Delta \boldsymbol{S_0} + \Delta \boldsymbol{S_c} \tag{14}$$

Where $\Delta \boldsymbol{S_o}$ is the soil P retention, $\Delta \boldsymbol{S_c}$ is the canal P assimilation, $\boldsymbol{I_c}$ is the P load flowing into the canal, $\boldsymbol{O_c}$ is the P load flowing out from the canal, $\boldsymbol{I_{Atm_C}}$ is the amount of P from atmospheric deposition over the canal, $\boldsymbol{I_{Drainage}}$ is the drainage load, $\boldsymbol{O_{Irrigation}}$ is the P load in irrigation. All terms are expressed in metric ton per year (mtons yr^{-1}). Equation 14 of the P budget model separating the sub-basin storage ($\Delta \boldsymbol{S_b}$) into soil P retention ($\Delta \boldsymbol{S_o}$) and canal P assimilation ($\Delta \boldsymbol{S_c}$) was used to estimate the amount of P accumulation in soil and P attenuated in canals respectively.

2.2.5 Canal Attenuation and Farm Impact Factors

Uptake of P by aquatic vegetation, precipitation in the water column and retention by sediments can markedly impact in-stream P flux (Darracq and Destouni, 2007). Simulating surface water dynamic attenuation processes is complex and requires data not available. Instead a first-order decay function (Equation 15) was used relating the downstream P concentration (C_x) to the concentration of water flowing into the canal (C_0) through an empirical attenuation coefficient (a) and a physical travel length (x)(Reddy et al., 1996).

$$C_x = C_0 \exp(-ax) \tag{15}$$

The a coefficient was estimated for each sub-basin, knowing the P concentrations in farm drainage (C_0), the location of discharging points and the total canal P assimilation (ΔS_c). The attenuation coefficient a for each canal was calculated to meet the conditional equation that the sum of the attenuated load of farms (including the urban runoff and C-139 basin inflow) would be equal to ΔS_c. The underlying assumption in equation 15 is that the discharge from each farm is isolated within the flow of the canal. The attenuation coefficients were subsequently used to differentiate the attenuation P load from farms and urban areas and to develop the impact factors as detailed below.

Dimensionless impact factors (I_1 and I_2) were also used to assess the degree of impact of the farms P loadings onto the STAs, using equations 16 and 17. I_1 takes into account the farm P load without attenuation and I_2 considers the farm net P load after attenuation in the canals. The two impact factors take into account the variances in farm areas and in Lake Okeechobee irrigation water P concentration. The two environmental indices were also normalized using equation 18.

$$I_1 = \frac{Farm\ P\ load}{\sum Subbasin\ ouflow\ load} \times \frac{EAA\ area}{Farm\ area} \times \frac{\sum Subbasin\ inflow\ load}{Subbasin\ inflow\ load} \tag{16}$$

$$I_2 = \frac{Farm\ net\ P\ load}{\sum Subbasin\ ouflow\ load} \times \frac{EAA\ area}{Farm\ area} \times \frac{\sum Subbasin\ inflow\ load}{Subbasin\ inflow\ load} \tag{17}$$

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \tag{18}$$

The impact factors were then classified into three classes - low, medium and high - with the ranges of (0.00-0.23), (0.24-0.57) and (0.58-1.00), respectively. Data classification was conducted using the Fisher-Jenks algorithm, minimizing each class's average deviation from the class mean and maximizing each class's deviation from the means of the other groups.

2.3 Results and Discussion

2.3.1 Water Budget and P Mass Balance

2.3.1.1 EAA Basin and Sub-Basins

Main components of the water budget, P mass balance and P flow-weighted concentration (P-FWM) for the EAA basin and for each sub-basin and its corresponding canal are presented in Table 2, Table 3 and Table 4. The median and minimum P concentrations were 58 and 8 μg L^{-1}, respectively indicating that values were within 10% of the true levels with 95% confidence interval following the uncertainty analysis presented by Kolasinski (2009). Data were tested for normality using Shapiro-Wilk test (p value<0.01) and the annual mean values were reported along with the standard error of the mean. The schematic diagram illustrating the P budget is shown in Figure 4.

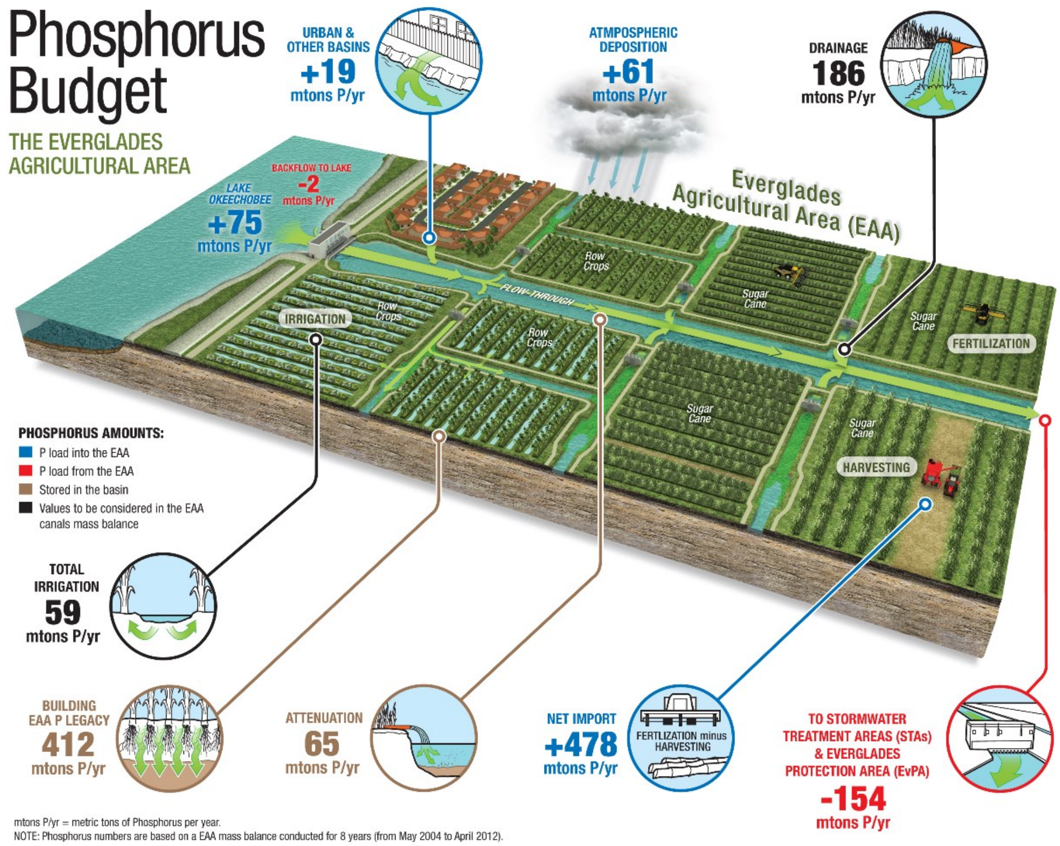


Figure 4- Schematic diagram of the phosphorus budget in the EAA, showing the P load into the EAA (blue), from the EAA (red), stored in the basin (brown), irrigation and drainage (black). Arrows used do not convey any cause / effect relationships.

The EAA is an area with a shallow water table and a low water storage capacity; Table 2 indicates that the change in water storage in the EAA averaged 450.3 ± 57.9 hm^3 annually where 376.6 ± 41.8 hm^3 of it was attributed to canal storage. On average, the total surface water outflow and ET each constituted 47% and 53% of the total outflows, respectively (Table 2). On average, the total surface water inflow and rain constituted 20% and 80% of the total inflows, respectively (Table 2).

Table 2- Main components of sub-basins and canals water budget (hm^3 yr^{-1}).

Sub-Basin (canal)	Surface Inflow			Surface Outflow		Rain	ET	Irrigation	Flow-Through	Drainage	ΔS_b	ΔS_c
	Lake	Urban	Other Basins	Backflow to Lake	Net Outflow							
S-5A (WPB)	108.0±19.3	14.6±2.4	0.0±0.0	0.0±0.0	260.1±43.2	561.2±43.9	330.4±4.6	82.7±14.6	25.3±7.1	335.5±43.0	93.3±10.0	114.3±15.9
S-2/S-6 (HBR)	77.7±13.0	27.1±3.9	0.0±0.0	4.3±1.5	311.3±26.8	636.1±32.0	342.2±5.4	69.1±11.2	8.6±2.0	341.4±35.3	83.2±22.5	60.4±14.7
S-2/S-7 (NNR)	145.4±24.4	0.0±0.0	0.0±0.0	8.1±2.9	250.2±42.4	561.4±29.4	292.5±4.7	119.8±18.1	25.6±10.1	324.4±40.5	155.9±25.9	90.7±20.7
S-3/S-8 (MM)	154.4±23.2	28.1±3.9	20.4±4.1	3.1±1.6	318.2±47.2	551.7±37.6	315.4±6.2	117.8±17.8	36.6±10.8	348.3±41.7	117.9±25.9	111.2±13.9
EAA	485.5±78.2	69.8±7.9	20.4±4.1	15.6±5.7	1139.8±146.8	2310.5±127.5	1280.4±20.9	389.4±58.7	96.1±28.6	1349.6±147.7	450.3±57.9	376.6±41.8

Results presented in Table 3 indicated that the average net outflow P loading to the STAs for the investigated WYs was 154.6 ± 23.4 mtons yr^{-1} originating from Lake Okeechobee flow-through, farms and urban areas. Farms, urban areas and the C-139 basin contributed 186.1 ± 26.1 mtons yr^{-1}, 15.6 ± 2.5 mtons yr^{-1} and 3.8 ± 1.0 mtons yr^{-1} to the canals, respectively. Lake Okeechobee flow-through contributed 16.4 ± 5.6 mtons yr^{-1} to the STAs (Table 3). Those values are comparable to the ones published by the SFWMD for the 8 WYs 2005-2012 (SFWMD, 2006-2013). Historically and before drainage, the annual P load to the entire Everglades from inflowing waters was estimated at 21 mtons P yr^{-1}.(Noe et al., 2001, Davis, 1994) Before constructing the STAs, the average annual P load to the EvPA from the EAA was approximately 175 mtons yr^{-1} for the period of 1978-1991 and 240 mtons P yr^{-1} for the period of 1992-1996.(Walker, 1999) During the investigated WYs, the P-FWM in surface inflow and outflow averaged 165 ± 16 µg L^{-1} and 136 ± 10 µg L^{-1}, respectively (Table 4). Lower P concentration in surface outflow could be misleading since the amount of P loading and the retention time are the key anthropogenic factors in the eutrophication process.(Smil, 2000) The average amount of P load in the surface outflow (157.2 mtons yr^{-1}) is about 1.6 times the amount of P load in the surface inflow (94.8 mtons yr^{-1}) (Table 3). The highest surface outflow P concentration was found in the S-5A sub-basin (203 ± 15 µg L^{-1}) and the lowest was found in the S-3/S-8 sub-basin (112 ± 14 µg L^{-1}).

Table 3- Main components of sub-basins and canals P budget (mtons yr^{-1}).

Sub-Basin (canal)	Surface Inflow			Surface Outflow		Atm. Deposit	Net Import	Irrigation	Flow-Through	Drainage	ΔS_c	$\Delta \boldsymbol{S}_b$	$\Delta \boldsymbol{S}_o$
	Lake	Urban	Other Basins	Backflow to Lake	Net Outflow								
S-5A (WPB)	24.4±4.3	7.9±1.7	0.0±0.0	0.0±0	52.8±10.8	15.3±0.4	119.4±0.0	18.9±3.2	5.5±1.6	70.2±10.9	30.7±3.3	114.2±7.9	83.5±10.4
S-2/S-6 (HBR)	11.4±2.9	4.2±0.6	0.0±0.0	0.7±0.3	35.5±4.6	16.6±0.3	137.2±0.0	10.1±2.6	1.3±0.4	49.8±7.4	19.2±4.0	133.1±3.4	113.9±6.7
S-2/S-7 (NNR)	21.3±5.5	0.0±0.0	0.0±0.0	1.4±0.5	30.9±4.6	14.6±0.3	104.4±0.0	16.9±4.1	4.4±2.0	34.8±4.9	7.0±3.6	107.9±4.1	100.9±4.6
S-3/S-8 (MM)	18.5±4.4	3.4±0.5	3.8±1.1	0.5±0.2	35.4±6.1	14.9±0.4	117.5±0.0	13.2±2.7	5.3±2.1	31.2±5.3	7.9±3.5	122.1±4.6	114.2±4.4
EAA	75.4±16.5	15.6±2.5	3.8±1.1	2.6±1	154.6±23.5	61.3±1.3	478.5±0.0	59.0±12.1	16.4±5.6	186.1±26.1	64.8±9.6	477.3±16.3	412.5±23.2

Table 4- P flow-weighted mean concentration (P-FWM) (µg L^{-1}).

Sub-Basin (canal)	Surface Inflow	Surface Outflow	Drainage	Irrigation	Flow-Through
S-5A (WPB)	263±27	203±15	205±15	231±17	212±13
S-2/S-6 (HBR)	149±19	115±9	140±11	138±23	147±26
S-2/S-7 (NNR)	146±23	125±13	106±4	136±23	145±27
S-3/S-8 (MM)	126±16	112±14	87±4	107±18	116±19
EAA	165±16	136±10	134±7	147±19	152±17

At a basin level and on average, P load from the surface inflow and atmospheric deposition represented 15% and 10% of the total P load into the EAA respectively, while the net P import contributed about 75% (478.5 mtons yr^{-1}, net P imports values per land use are presented in Table 5) of the total P load into the EAA (Figure 5). It is worth noting that the P load in the surface inflows was originating from Lake Okeechobee – water used for irrigation and for flow-through (75.4 mtons yr^{-1}, equivalent to 80% of the total P load in the surface inflow) and from the urban areas and the C-139 basin (19.4 mtons yr^{-1}, equivalent to 20% of the total P load in the surface inflow).

Table 5- EAA P net imports per land use for WYs 2005 – 2012.

Land Use	Net Import Coefficient (kg P ha^{-1} yr^{-1})	Area (ha)	Net Imported Load (mtons yr^{-1})
Residential -Low Density	9.9	195.6	1.9
Residential -Medium Density	22.9	591.0	13.5
Residential -High Density	9.1	148.3	1.4
Other Urban	1.6	3383.9	5.4
Golf Course	32.3	56.3	1.8
Improved Pasture	4.4	746.5	3.3
Truck Crops	32.8	3.5	0.1
Field Crops	6.9	19.0	0.1
Sugarcane	3.4	133478.7	448.5
Citrus	8.0	44.4	0.4
Barren Land	0.0	4352.3	0.0
Tree Nurseries	18.7	105.9	2.0
Rangeland	0.0	383.0	0.0
Forested -Deciduous	0.0	17.7	0.0
Water Bodies	0.0	3178.2	0.0
Sum			478.4

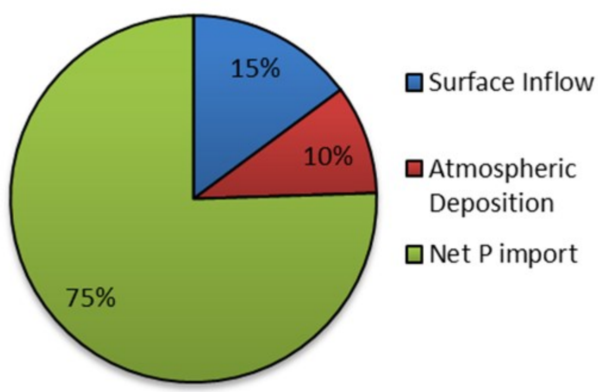


Figure 5- Percent contribution of the surface inflow, atmospheric deposition and net import to the total P load into the EAA.

The term representing the change in soil P retention (ΔS_o) incorporated the internal processes of soil P mineralization and immobilization. Soil P retention is a measure of soil buffering capacity for P and the mass of additional P annually stored in soil systems as the result of anthropogenic activities(SWAT, 2007). Results presented in Table 3 indicate that annually the EAA soil is retaining a P load of approximately 412 mtons yr^{-1} equivalent to 2.9 kg P ha^{-1} yr^{-1} while CH2M-Hill(1978) estimated this value at about 9.7 kg P ha^{-1} yr^{-1} for one farm. The positive change in the soil P retention term is an indicator of surplus P and soil P accumulation or immobilization (Bouwman et al., 2011) leading to the build-up of legacy P. Reddy et al.(2011) reported a current P storage of 59 mtons km^{-2} (triple the P amount per unit area of any other Greater Everglades ecosystem basins) in 0-10 cm of the EAA soil due to a combination of peat oxidation (soil subsidence) and long-term fertilizer application amounting to a total of 123,000 mtons of P stored in the soil. Castillo et al.(2008) reported a 317 mg P kg^{-1} difference between natural areas and cultivated soils after 50 years of cropping sugarcane. The current and continuing rate of building-up legacy P in the EAA may pose a significant long-term impact on the nutrient status of the downstream ecosystems. It is worth noting that in the EAA, the labile P (P not strongly adsorbed in the soil and entering the soluble phase relatively quickly) pool is averaging less than 0.5% of total P with a great potential to be exported in the runoff (Wright, 2009). Reddy et al.(2011) estimated that the current legacy P in the EAA would support the 170 mtons yr^{-1} load to the STAs and WCAs for the next 47–118 years.

2.3.1.2 EAA Canals

Drainage P load is the amount of P discharged into the canal system before undergoing any attenuation process, thus representing the amount of P moving from farms to the canals. Drainage P load is significantly correlated to the hydrologic and water management properties such as the BMPs, pump-rainfall ratio, farm size, land use, soil depth and irrigation P load (Lang et al., 2010, Grunwald et al., 2009). P load from surface inflows and from drainage contributed 34% and 66% of the total P load to the canals, respectively. The P loading in irrigation is estimated at 59.0 ± 12.1 mtons yr^{-1} corresponding to 32% of the P load in drainage (Table 3) while there is no significant difference between the P concentration in irrigation and drainage (Table 4). Based on the mean values presented in Table 2 and Table 3, MM canal received and discharged the highest volume of water (552.5 and 441.3 hm^3 yr^{-1}) while WPB canal received and discharged the highest P load (102.5 and 71.7 mtons yr^{-1}). While application of fertilizers is often cited as a primary cause of high P loading from agricultural runoff (Sharpley et al., 2000) others would argue that extensive oxidation of organic-rich soil in the EAA contributes a large portion of P to drainage water (Izuno et al., 1991). Using uranium isotopes as indicators of fertilizer-derived P, Zielinski(2000) demonstrated that dissolved P in agricultural drainage from the NNR and MM canals are mainly of a fertilizer origin.

Table 2 indicates that farms runoff collectively drained 1349.6 ± 147.7 hm^3 annually while the rainfall in the EAA was about 1.8 times the ET with a net rainfall of 1031.1 ± 106.6 hm^3 yr^{-1}. Since Lake Okeechobee water is usually used for irrigation purposes during the dry season, the ratio of runoff volume to the net rainfall during the wet season is 130%. Comparing this ratio to the 240% value reported by SFWMD(1999) indicates that since 1999, water retention has been gradually implemented as a working management strategy and should be enforced to control soil oxidation and subsidence as well as to extend the economic life of cropland soils (Aillery et al., 2001).

Canal P assimilation (ΔS_c) is the mass of P stored in the canal (sediments and water) and is correlated to P inputs from drainage ($R^2 = 0.68$ as indicated in Figure 6) representing ΔS_c values for the four canals during the 8 WYs). Figure 6 shows that during three WYs, MM and NNR canals acted as a P source (negative ΔS_c values). A greater ΔS_c is desirable since it helps reducing the P loads to the STAs. A higher ΔS_c also reflects the higher potential of the canal to act as a sink that could occur by P flux from water column to sediments. The canals assimilated 64.8 ± 9.6 mtons yr^{-1} and the mean annual values of ΔS_c ranged from 30.7 ± 3.3 mtons yr^{-1} for WPB canal (acting as an overall sink) to 7.0 ± 3.6 mtons yr^{-1} for NNR canal (Table 3). The obtained P attenuation coefficients and their corresponding 90% confidence intervals for WPB, HBR, NNR and MM canals are 3.85×10^{-5} (2.80×10^{-5}–5.17×10^{-5}), 2.61×10^{-5} (1.17×10^{-5}–3.46×10^{-5}), 1.15×10^{-5} (2.80×10^{-7}–2.65×10^{-5}) and 1.30×10^{-5} (1.61×10^{-6}–2.77×10^{-5}), respectively. ΔS_c values were also positively correlated to the attenuation coefficients with the highest value for WPB canal and the lowest value for NNR canal. Among the canals, MM and NNR canal sediments attenuated the lowest P loadings and showed an overall state of quasi-equilibrium with the P concentration in the water column. This result is in agreement with Das et al.(2012) reporting that WPB canal was acting as a P sink while the MM canal sediments released a small quantity of P ranging from 0.4 to 1.2 mtons yr^{-1}. Using the attenuation coefficients, the mean attenuation P load from farms and urban and C-139 basin were estimated at 55.1 and 9.7 mtons yr^{-1} respectively. To calculate the farm P drainage contribution to the total outflow P load (157.2 mtons yr^{-1}), one should subtract the farm attenuation load (55.1

mtons yr^{-1}) from the P loads in the drainage water (186.1 mtons P yr^{-1}), leading to a total value of 131 mtons yr^{-1}, representing 83% of the total outflow P load.

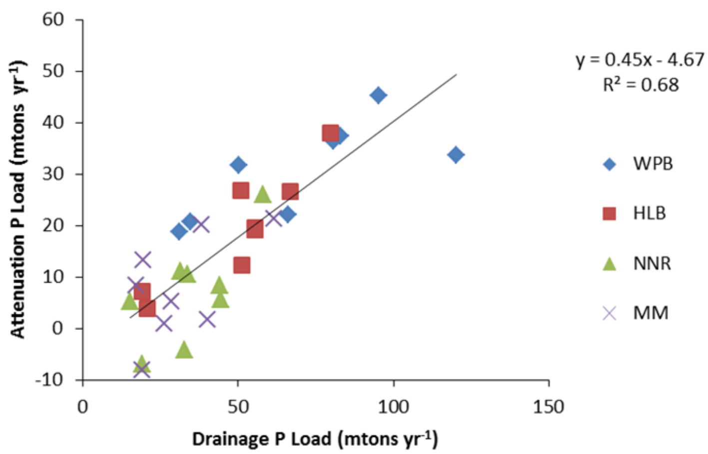


Figure 6- Relationship between canal P attenuation (ΔSc) and P inputs from drainage for the four canals during the eight water years. Slope is significantly different from zero with $p<0.0001$.

Canal sediments can behave as a sink or source for P depending on water column and sediment physicochemical properties (Reddy et al., 1995). Despite the fact that WPB, NNR, HBR, and MM canal sediments have similar physicochemical properties in terms of organic matter, pH, and density (Das et al., 2012) they function in a different way in terms of P release / retention. This could be due to greater interactions of runoff waters with fragments of limestone and shell layers in the WPB sediments, thus increasing P assimilation in this canal (Lang et al., 2010). Another possible reason could be the lower P concentrations and higher drainage water volumes in the S-3/S-8 basin, when compared to the S-5A basin. The lowest P-FWM was obtained in the S-3/S-8 basin surface water inflows and drainage (126 and 87 μg L^{-1}) as indicated in Table 4. A low P-FWM value (83 μg L^{-1}) was also reported for MM canal by Daroub et al.(2007) along with the highest ratio of pump to rainfall for the MM canal (0.73) and the highest drainage in terms of unit area volume for the S-3/S-8 sub-basin.

2.3.1.3 Seasonal Analysis

EAA water and P budgets were also analyzed during the wet and dry seasons of WYs 2006-2012 and they are presented in Figure 7 and Figure 8. On average, 80% of rainfall and 62% of ET occurred during the wet season. Furthermore, 80% of the drainage volume and 82% of the P load in the drainage occurred during the wet season. The high P load release during the wet season could be attributed to the fact that flooding organic soil increases P release in the drainage water up to 4 to 8 times (Sanchez and Porter, 1994). This high P release in the drainage water during the wet season was correlated with the high rainfall level and was not correlated with surface inflow waters. The surface outflow water and P load were substantially greater during the wet season (80%) while the surface inflow water and P load did not show a significant difference between the wet and dry seasons.

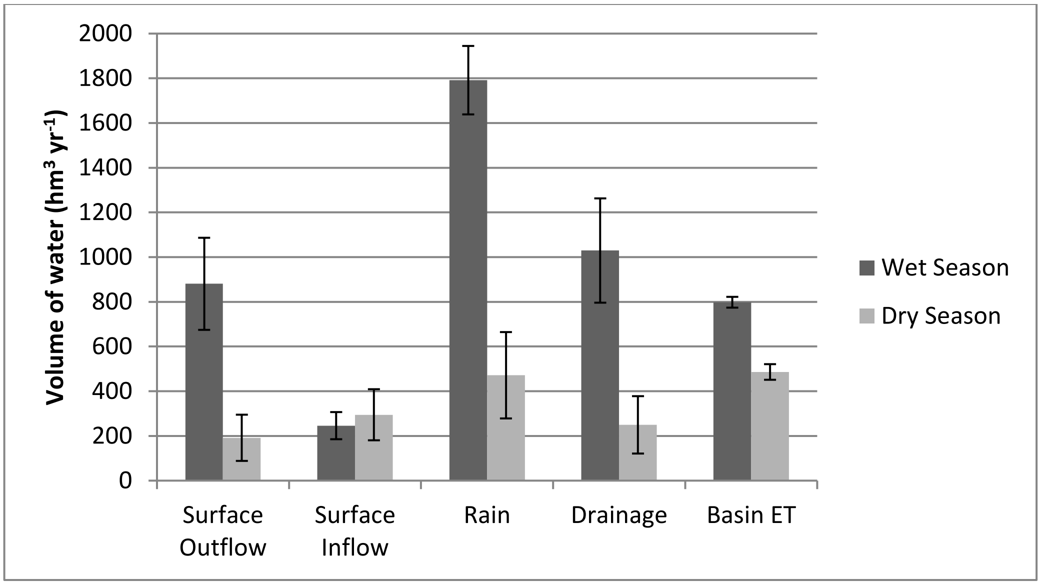


Figure 7- Mean seasonal water budget components in the EAA.

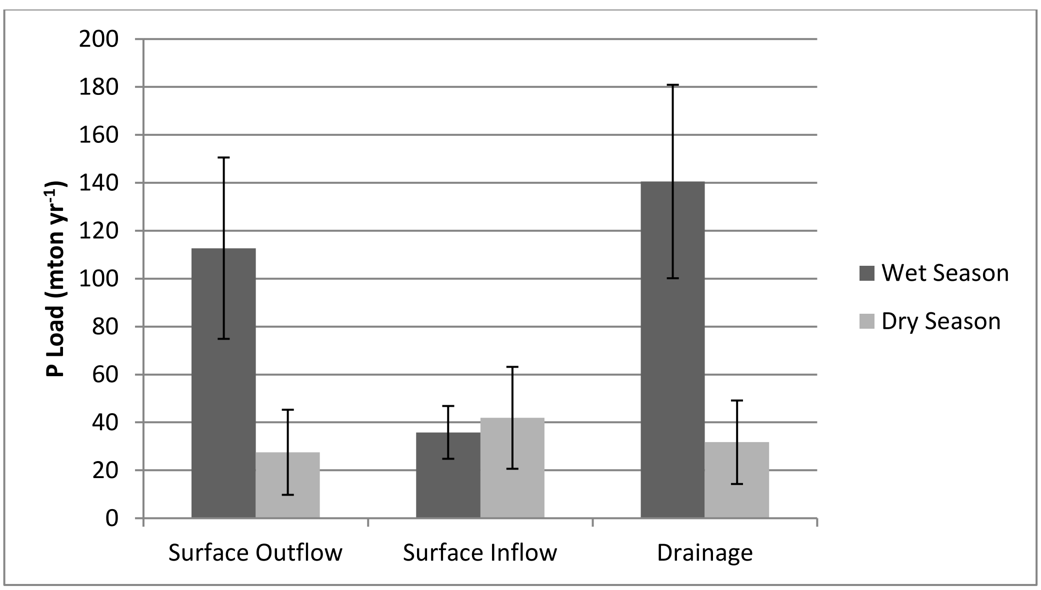


Figure 8- Mean seasonal P load budget components in the EAA.

2.3.2 Impact Factors

The impact factors, equivalent to a P risk assessment index, as defined are important indicators and would be a new cost effective tool to identify and select critical areas within an agricultural watershed, contributing disproportionate higher P loadings to the ecosystem. The first impact factor (I_1) is shown in Figure 9A illustrating the dimensionless contribution of the P load from drainage per farm and per unit area to the total outflow P load, while also considering each sub-basin inflow P load to compensate for the farms receiving higher concentration water from lake Okeechobee.

The I_1 factor average value was 0.23 and the upper 75th percentile and 90th percentile were 0.30 and 0.47, respectively. From the 41 farms in the S5A sub-basin, 73%, 20% and 7% of the farms displayed a low, medium or high I_1 factor, respectively. A similar trend was observed in the S2/S7 sub-basin with 65%, 33% and 2% of the farms characterized by a low, medium or high I_1 factor, respectively. In the S-2/S-6 sub-basin with 58 farms (highest number of farms), 52% of farms displayed a medium I_1 factor and 12% had a high I_1 factor while the S-3/S-8 sub-basin with 32 farms (lowest number of farms), 91% of the farms had a low I_1 factor. The eleven farms identified in Figure 9A with a high I_1 factor level contributed 9% (17 mtons yr^{-1}) of the total drainage P load to the canals while their collective area represented less than 3% (4,792.8 ha) of the total EAA acreage. Fifty one farms with a medium I_1 factor level, contributed 35% (66.2 mtons yr^{-1}) of the total drainage P load to the canals while their collective area represented less than 20% (38,461.6 ha) of the total EAA acreage. Therefore, targeting farms with a high and a medium I_1 factor level with further scientific investigations could explain the parameters affecting the P loadings variability among farms such as the adequacy of the BMP types implemented on these farms, history of cultivation and crop rotation, soil properties and mineralization, farm drainage system characteristics, duration of flooding, microbial activity within the soil, to name only a few. More effective and improved P control farming practices would ultimately control the amount of P introduced into the canal systems, this could be achieved if the storage, fate, and transport of P in soils, ditches and canals are well understood (Flaig and Reddy, 1995).

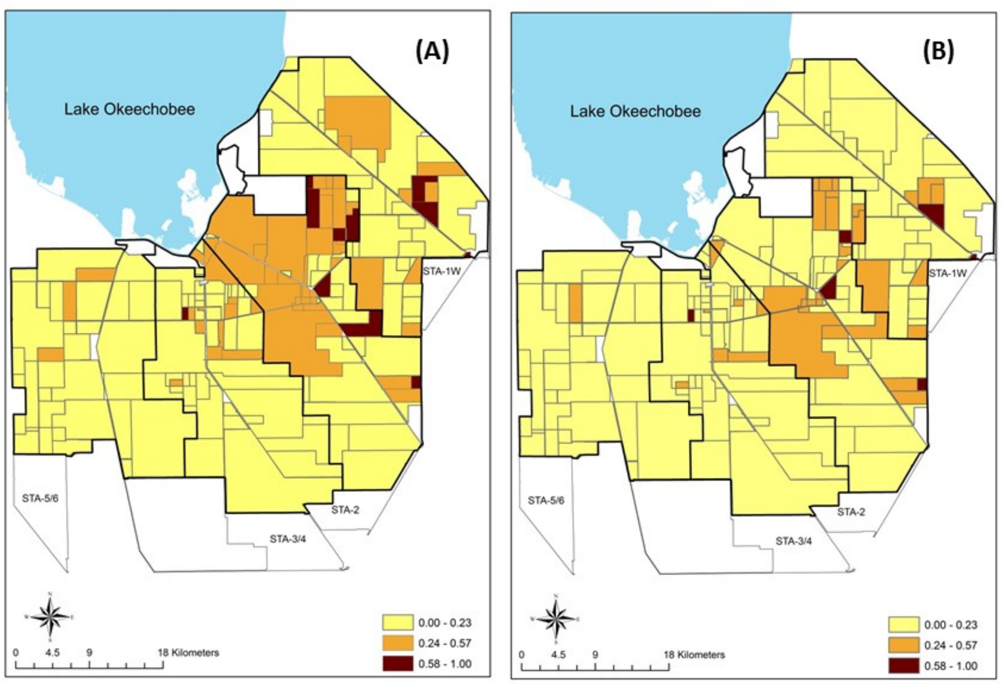


Figure 9- Classification of the EAA farms based on their impact factors I_1 (A) and I_2 (B).

In order to understand the impacts of canal attenuation, a second impact factor (I_2) was used following the same classification as I_1 and the results are illustrated in Figure 9B. The I_2 factor average value was 0.17 and the upper 75th percentile and 90th percentile were 0.21 and 0.34, respectively. The main difference between the two factors is that the P load from drainage per farm and per unit area after attenuation (taking into account the distance to the outlet) was used for the calculation of the I_2 factor and not for the calculation of the I_1 factor. Figure 9B confirms the function of canal P assimilation in reducing the impact of farm P loadings on the total outflow P loadings. Indeed, canal P attenuation had an important effect on the results, as 5 farms were de-classified from having a high I_1 factor to a medium I_2 factor and 13 farms were de-classified from having a medium I_1 factor to a low I_2 factor medium. The majority of these de-classified farms was located in S2/S6 sub-basin; the further away from the outlet, the higher the attenuation. The 44 farms identified with a high or a medium I_2 factor level contributed 28% (51.8 mtons yr^{-1}) of the total P load reaching the STAs while their collective area did not exceed 11% (21,549 ha) of the total EAA acreage.

2.3.3 Environmental Significance

The P budget analysis at the basin level indicated that P input from fertilizer, atmospheric deposition and irrigation exceeded the P removal from harvesting and drainage, suggesting that P is building up at a conservative rate of 412.5 mtons yr^{-1}. Results indicated that all the canals acted as a P sink, assimilating a total of 64.8 mtons yr^{-1}. The average ratio of P assimilation to P load in drainage is approximately 35% with the highest value for WPB canal (43%), followed by the HLB canal (38%) and the NNR canal (20%)

and the MM canal (25%). Results obtained from the impact factors demonstrated the role of canal P assimilation in reducing the drainage P load impact on the P load at the sub-basin outlet particularly in the S-2/S-6 and S-5A sub-basins, results independent from the effects of the farm size or P load in the surface inflows. Sixty two farms were identified with a high and a medium I_1 factor level contributing 44.5% (83.1 mtons yr^{-1}) of the total drainage P load to the canals while their collective area represented less than 23% (43,254.5 ha) of the total EAA acreage. Therefore, optimizing the BMP strategies on these farms might assist in significantly reducing the P level in the drainage water, further minimizing thus the P levels in the basin runoff and the environmental impacts on the sensitive downstream wetlands areas.

3. SUGARCANE CROP MAPPING USING TIME SERIES OF LANDSAT NDVI DATA

3.1 Introduction

With the green revolution, agriculture has reshaped the socioeconomic landscape around the world (Tilman et al., 2002). Agricultural production in developing countries has increased by 3.4% annually over the last two decades (Angelsen, 2010). Intensive agriculture in the Brazilian Amazon grew by more than 3.3 million ha during 2001-2004 (Morton et al., 2006). During the last 100 years, land use in southern Florida has significantly changed, shifting from a natural wild landscape to highly farmed areas (Solecki and Walker, 2001). The vast decadal growth in agricultural fields in southern Florida led to severe environmental changes that have not been limited to marked reductions in wildlife populations (Noe et al., 2001). It is fairly well established that some correlation exists between non-point source pollution from agricultural runoff and land use. (Bhaduri et al., 2000, Perry and Vanderklein, 2009, Basnyat et al., 2000, Tong and Chen, 2002). Therefore pollution from agricultural runoff has geospatial characteristics and it may vary with land-use features. Rice et al (2002) evaluated BMP strategies to reduce the load of contaminants under different sugarcane cropping system including cropped to sugarcane, sugarcane-vegetable and sugarcane-rice or fallow. Considering the importance of the environmental impact of agriculture, researchers and decision makers in environmental management need tools that can provide trustworthy and reproducible information on agricultural land use including crop types and crop rotation. This type of information is generally well-guarded by farmers. Even the United States' Cropland Data Layer program, which provides state-level crop cover classification data with accuracies ranging from 85% to 90%, does not provide detailed crop information (Boryan et al., 2011).

The impacts of sugarcane cultivation (runoff, leaching and irrigation) on water quality and aquatic ecosystems are well established (Cheesman, 2004). Therefore, low-cost and high-accuracy identification of sugarcane areas and accurate forecasts of crop acreage using remote sensing (RS) images for watershed management purposes, coordination among farmers and BMP implementation has been the subject of several studies. Abdel-Rahman et al. (2008) reviewed the results of the application of RS techniques for classification, thermal age group identification, varietal discrimination and yield prediction of sugarcane fields. Schmidt et al. (2001) summarized findings linked to the use of various RS sensors (Landsat, NOAA AVHRR, SPOT 4, DMSV) for sugarcane mapping. The Schmidt et al. (2001) study showed the potential of using the NDVI (Normalized Difference Vegetation Index) value, which measures the absorption of red light by plant chlorophyll and the reflection of infrared radiation by water-filled cells, as an index of crop condition. The link between sugarcane NDVI variations and plant phenology has been the subject of many studies (Begue et al., 2010, El Hajj et al., 2009, Baghdadi et al., 2010, Wardlow and Egbert, 2008). In 2006, Xavier et al. presented a cluster analysis using the multi-temporal Enhanced Vegetation Index based on MODIS data to discriminate sugarcane from planted forested areas, soybean crops, peanuts, water bodies, and urban areas in Sao Paulo, Brazil. Object based image analysis and data mining techniques were applied to multi-temporal Landsat images for sugarcane mapping over the same area by Vieira et al. (2012), who noted an overall accuracy of 94%. While these procedures provided accurate and consistent results they require substantial expertise and interpretation and are difficult to execute.

Among the many pattern recognition algorithms that have been used to perform land-use classification using RS imagery, decision tree classification techniques have substantial advantages because of their flexibility, intuitive simplicity and computational efficiency (Friedl and Brodley, 1997, Pal and Mather, 2003). Decision Tree Analysis (DTA) is a rule-based and non-parametric classifier that can produce highly accurate results based on a variety of spectral and auxiliary data (Lawrence et al., 2004). Using auxiliary data, in addition to the RS images, it has the potential to increase classification accuracy (Lawrence and Wright, 2001). DTA forms dichotomous decision trees using continuous or categorical data that can be applied to a single image or a stack of images. The result is made up of a series of decisions that are characterized by their representation of developed knowledge (Quinlan, 1986). The term knowledge refers to behavior patterns for each class of interest. This study details the application of DTA to discriminate sugarcane from other land use classes such that the methodology can be extended to any plantation type. Our primary objective was to present a simple yet novel approach to discriminate sugarcane from other crops by incorporating time series of satellite images that include information on crop growth cycles into DTA. Two secondary objectives include 1) comparing the performance of DTA with that of a supervised artificial neural network (ANN) for sugarcane mapping using RS imagery and 2) developing a method to overcome a severe problem of partial cloud cover in optical remote sensing of agricultural fields. The latter objective was crucial for conducting the study because sugarcane is a perennial crop that thrives in tropical areas (Verheye, 2010) where clouds are common occurrences, making RS image processing difficult. Removing cloud cover can be a painstaking process, as both the cloud cover and their associated shadows need to be eliminated before any analytical process is performed (Tiner et al., 2015). Nevertheless, the automated scheme employed in this study overcame the above constraints. Developing a methodology for cloud and cloud shadow identification and removal was the secondary objective of this research. The developed methodology was tested in this study. To the best of my knowledge, this approach has never been used before and will be useful for agricultural environmental management.

3.2 Methodology

3.2.1 Study Area

The study area includes one sub-basin (S5A) of the EAA located in southern Florida and has the area of 540.52 km^2 (Figure 10). The EAA is under intensive agriculture and produces 52% of the United States' sugar (Heynen et al., 2007). Sugarcane is grown in rotation with sweet corn, rice, or leafy vegetables, or the land is kept fallow (Morris and Gilbert, 2005). Land use for crops grown in the EAA in previous years and changes in land use over time could not be determined; accurate records are not maintained by the county or by government agencies (Morris and Gilbert, 2005).

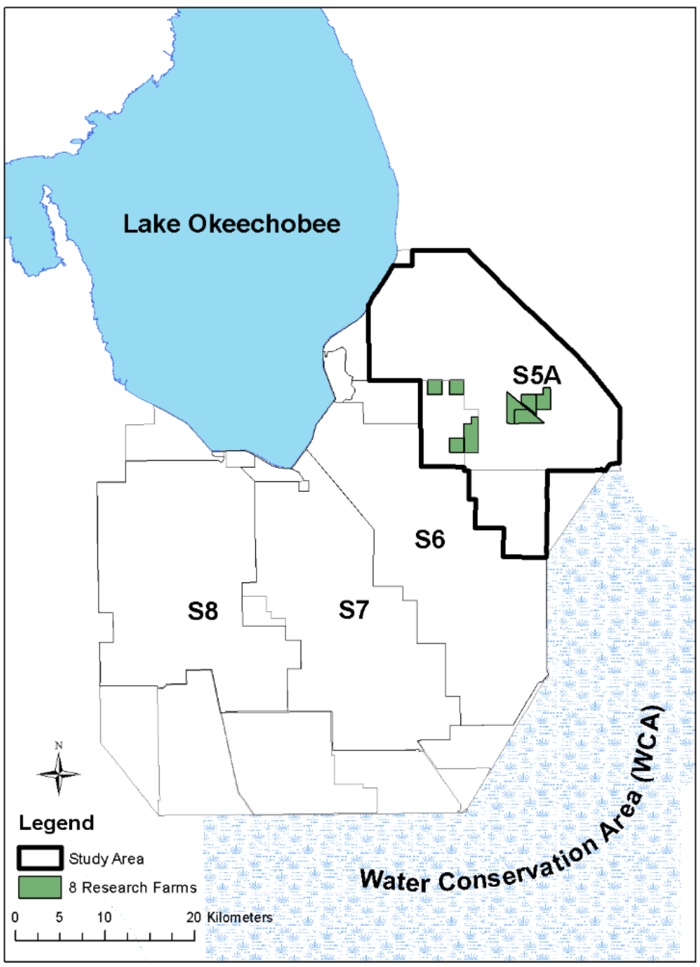


Figure 10- Map representing Lake Okeechobee and the region south of Lake Okeechobee. The 8 research farms are represented in green.

3.2.2 Sugarcane Crop Cycle

Sugarcane's spectral behavior is a function of its phenological dynamics during its biological cycle (Vieira et al., 2012). Sugarcane planting in the EAA occurs from late August through January, depending on local climate and variety used (Table 6). Typically, a sugarcane field is replanted every two to four years. After the field has been harvested the first time, a second crop of stalks, called a ratoon, grows from the old plant stubble. The second crop is harvested about one year after the first harvest (Baucum et al., 2006). The ratoon cane is burned prior to harvesting. On average, three annual crops are harvested from one field before it is replanted. When annual production declines to an unacceptable level, the ratoon cane is harvested and the field is immediately tilled to make sure that the stubble is uprooted. The land is then prepared for replanting with new seed cane ("successive planting"); the land may also be planted using another crop such as rice or sweet corn ("fallow planting"), or the land may be kept fallow (either chemically treated to suppress weeds or flooded) (Morris et al., 2004). The harvest season generally starts in late October and continues through mid-April. Given no damaging effects from freezes, yields are typically highest after December (Baucum et al., 2006).

Table 6- Phenological phases of sugarcane and the NDVI value corresponding to each phase.

Dry Season							Wet Season					Dry Season				
Sugarcane Growing										Sugarcane Harvesting						
Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
			Fallow (NDVI <0.5)													
				Sugarcane (NDVI >0.5)												

Due to the timing of the seasonal developmental stages of sugarcane, it is possible to distinguish the number of fields with first-harvest sugarcane and those with second-, third-, or fourth-harvest sugarcane in a single satellite image acquired on a given date. As the fields are transformed after three or four years of successive harvest, the field is left fallow or given over to fallow planting. This frequent change highlights the need for multi-temporal image acquisition to enable accurate classification of the growth cycle stage of sugarcane fields.

3.2.3 RS Imagery and Processing Approach

The EAA was completely within the Landsat-8 OLI scene located at WRS-2 path 15, row 42 for the year 2014. However, in previous years, the same scene (WRS-2 path 15, row 42) from Landsat-5 TM and Landsat-7 ETM$^+$ did not cover the study area, and a small area fell inside the scene located at WRS-2 path 15, row 41 (Figure 11). We did not mosaic the two scenes (WRS-2 path 15, row 41 and WRS-2 path 15, row 42) because this process was computationally expensive for the multi-temporal images. Therefore, the analysis was performed separately on each scene.

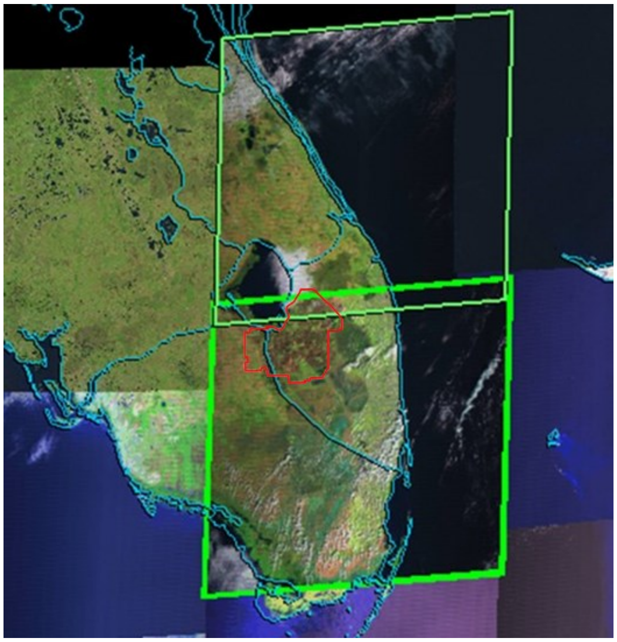


Figure 11- Landsat-7 ETM$^+$ imagery. The green borders show the scenes employed (WRS-2 path 15 row 41 and WRS-2 path 15 row 42) (U.S. Department of Interior and U.S. Geological Survey, 2015). The red border represents the EAA basin.

Table 7 lists the dates that were selected to capture the temporal variations. A preliminary visual image analysis was performed to verify the geo-referenced images, and then a subset of each image was extracted to include the area of interest. All the non-agricultural areas, including buildings, canals, roads, ponds, and lakes, were classified as urban using the Mahalanobis Distance Algorithm (Xiang et al., 2008) by means of training data identified in high-resolution NAIP (National Agricultural Imaging Program) images. Since the spectral compositions of these classes will not change over time, the relationships between informational classes and spectral classes are constant, and the relationships defined using one image apply in others.

Table 7- Selected dates used to access the geo-referenced Landsat-5, Landsat-7, and Landsat-8 level 1 images from 2011 to 2014.

Landsat-8 OLI	Landsat-7 ETM$^+$	Landsat-5 TM
2 Nov 2014	20 Sep 2013	10 Nov 2011
15 Sep 2014	28 Mar 2013	21 Jul 2011
29 Jul 2014	23 Dec 2012	18 May 2011
11 Jun 2014	5 Nov 2012	10 Jan 2011
26 May 2014	18 Sep 2012	
24 Apr 2014	30 Jun 2012	
7 Mar 2014	27 Apr 2012	
18 Jan 2014	10 Mar 2012	
17 Dec 2013	5 Jan 2012	
11 Aug 2013	15 Sep 2011	
23 May 2013	7 Mar 2011	
21 Apr 2013	18 Jan 2011	

A mask was generated based on this classification to exclude urban areas from further analysis. A preprocessing of RS images was then performed prior to vegetation extraction to remove noise and increase the interpretability of the image data. In the context of digital analysis of remotely sensed data, preprocessing is mainly performed to make time series of images spectrally compatible. All images were first radiometrically calibrated, and then an atmospheric correction was applied using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube) method in ENVI's atmospheric correction module (Spectral Sciences Inc, 2009). From each image, the visible red and NIR (near infrared) bands were used to calculate the NDVI. The proposed approach includes the following major steps: training set generation, data mining, interpretation and evaluation of the decision tree, classification of multi-temporal data, and validation of the classification on independent samples using confusion matrix methods and performing an accuracy assessment following the methodology described by Congalton et al. (2008).

3.2.4 Cloud and Cloud Shadow Removal Procedure

A single sugarcane growth and harvest cycle lasts several months. The typical time gap between two cloud-free Landsat images is too long to sample each stage of planting, growth and harvest. This is because, in tropical and subtropical areas, cloud-free optical satellite images are scarce. To mitigate this problem, a procedure for removal of clouds and cloud shadows was developed, implemented, and automated for processing large numbers of RS images.

Significant work has been devoted to cloud and cloud shadow identification (Shen et al., 2014, Oreopoulos et al., 2011, Zhu and Woodcock, 2014) . In the present study, the Fmask algorithm developed by Zuo et al. (2012) was used to identify the contaminated pixels. The presence of well-defined geometric field borders (canals and ditches in an agricultural area) facilitated the procedure; I assumed that the land use within field borders in the EAA (approximately 800 m by 800 m) is homogenous. This simplifying assumption enabled the estimation of a replacement for the spectral responses of the contaminated pixels. To interpolate over the cloud and cloud shadow contaminated pixels, first the percent of cloud and cloud shadows cover for each image in the area of interest was calculated. The S5A sub-basin was then divided into four blocks, and any image with greater than 50% contaminated pixels in a block or having excessive cloud cover was removed from the data set. The remaining set of images contained pixels affected by small, isolated clouds. The contaminated pixels within each field border were then masked out and then their digital values were filled in using the spectral response of the nearest cloud-free pixel within the same field border. This procedure substitutes the spectral properties of the contaminated pixel with the most likely values. The procedure was repeated for each field until all the contaminated pixels were removed from the data set.

3.2.5 DTA Procedure

The basic structure of a decision tree consists of one root node, a number of internal nodes and finally a set of terminal nodes. Each decision divides the data into one of two possible classes. The data are recursively divided down the decision tree according to the defined classification framework. Each decision rule is represented by a tree node that defines a probability distribution in the space of possible decisions and the possible outcomes, which are associated with branches emanating from the node. We defined the three classes of interest as 1) Sugarcane; 2) Mixed crops; 3) Fallow. According to the availability of the RS images described by Table 7, the NDVI temporal profiles for the years 2011 and 2012 each contained 7 bands, the profile for the year 2013 contained 6 bands, and the profile for the year 2014 contained 8 bands.

The decision tree was developed based on Table 6, in which the behavior of fallow fields and the phenological behavior of sugarcane based on NDVI values are presented. In this phase, a data mining technique was employed to extract patterns of interest for the effective production of knowledge. Examination of the growth pattern of sugarcane and the training data revealed that most sugarcane fields had NDVI values greater than or equal to 0.5 from early March through late November, while fallow fields had a consistently small NDVI (less than 0.5) from February through August. Late planted sugarcane may start in early April or early May and has a large NDVI (greater than or equal to 0.5) until late September or December. Early harvested sugarcane also showed a very large NDVI (greater than or equal to 0.7) during June or July. Although only the sugarcane class of information was developed, further discrimination of sugarcane into ordinary sugarcane, early harvested sugarcane and late planted sugarcane is feasible by means of DTA. Finally, the mixed crop class of information was defined as a pattern other than that of sugarcane or fallow fields (Figure 12). In other words, if a pixel is not classified as sugarcane or fallow, then it is defined as belonging to the mixed crop class.

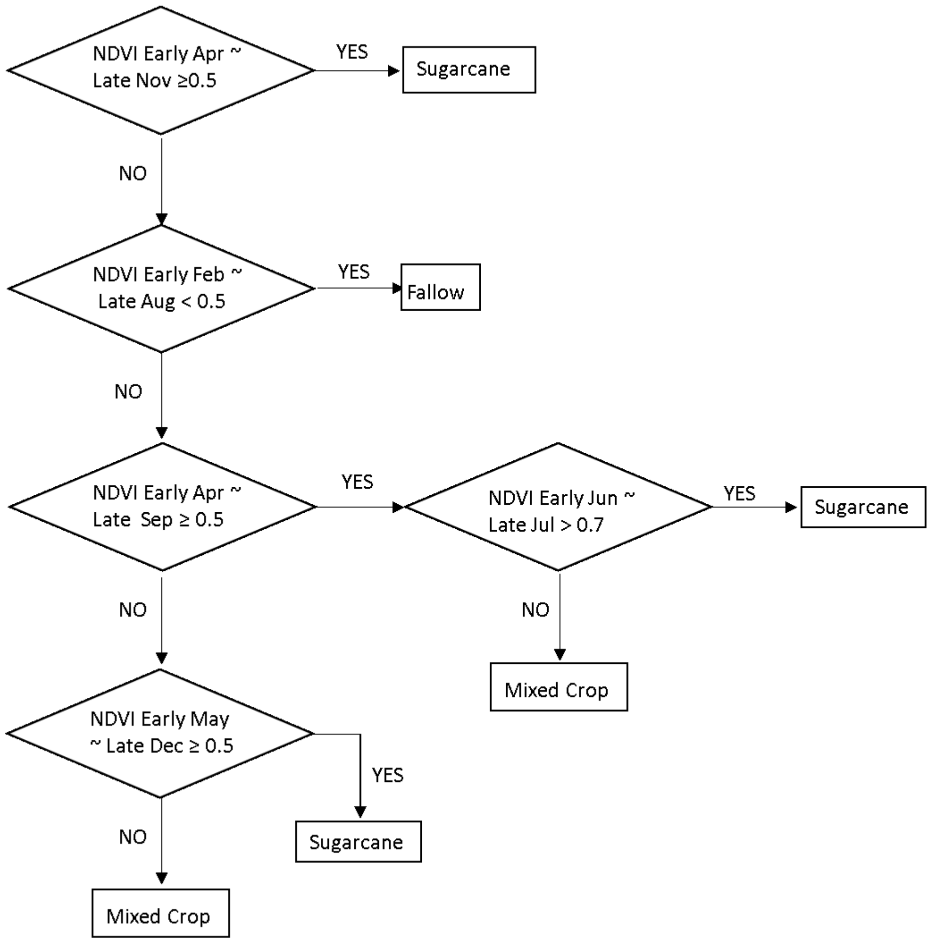


Figure 12- Schematic representation of the decision tree for identifying the three classes based on multi-temporal NDVI.

3.2.6 Artificial Neural Networks (ANN)

We used an ANN supervised classification following the back-propagation method to map sugarcane, mixed crops and fallow fields in the S5A sub-basin. ANN is a non-parametric method and has proven to be a powerful technique for machine learning (Towell and Shavlik, 1993). We then compared the results to those of DTA, which shed light into the structural differences between the ANN procedure, which is essentially a black box, and the understandable decisions made by DTA (Pal and Mather, 2003). The ANN classification was carried out for the years 2012, 2013 and 2014. All the ground truth data are located in the scene located at WRS-2 path 15, row 42. Therefore, no training data were created for the scene located at WRS-2 path 15, row 41, which leads to limitations in the ANN analysis of this scene.

Both the DTA and ANN are non-parametric methods which is very useful because many of the parametric classifiers (e.g. maximum likelihood) requires severe statistical assumptions such as the assumption that the training data display multivariate normal frequency distribution (Campbell and Wynne, 2011). In this study those assumptions were normal frequency assumptions were not met and therefore the results of the parametric methods would not be trustworthy in this case and non-parametric methodology is preferred.

3.2.7 Ground Truth Data

Daroub et al. (2014) reported land use information (sugarcane, fallow and mixed crops) from 8 research farms in the study area with the total area of 25.78 km^2 (about 5% of the study area) that had been monitored continuously by since January 2011, and that provided total concurrent ground truth data of 76,477 pixels for the three years of the study (Figure 10). The ground truth data for the year 2011 served as training data, and the rest (covering the years 2012, 2013 and 2014) were used for accuracy assessment analysis for DTA. For the ANN analysis, I randomly divided the ground truth data for the years 2012 to 2014 into two categories, training data and reference data, for each year. Therefore, the number of ground truth pixels used in the accuracy assessment of the ANN procedure is less than that used to evaluate the DTA method.

3.3 Results

The results of the DTA classification for the years 2012 through 2014 are illustrated in Figure 13A, Figure 13B and Figure 13C, respectively. DTA was used to define the classes of land use, which were “sugarcane” “mixed crops” and “fallow”.

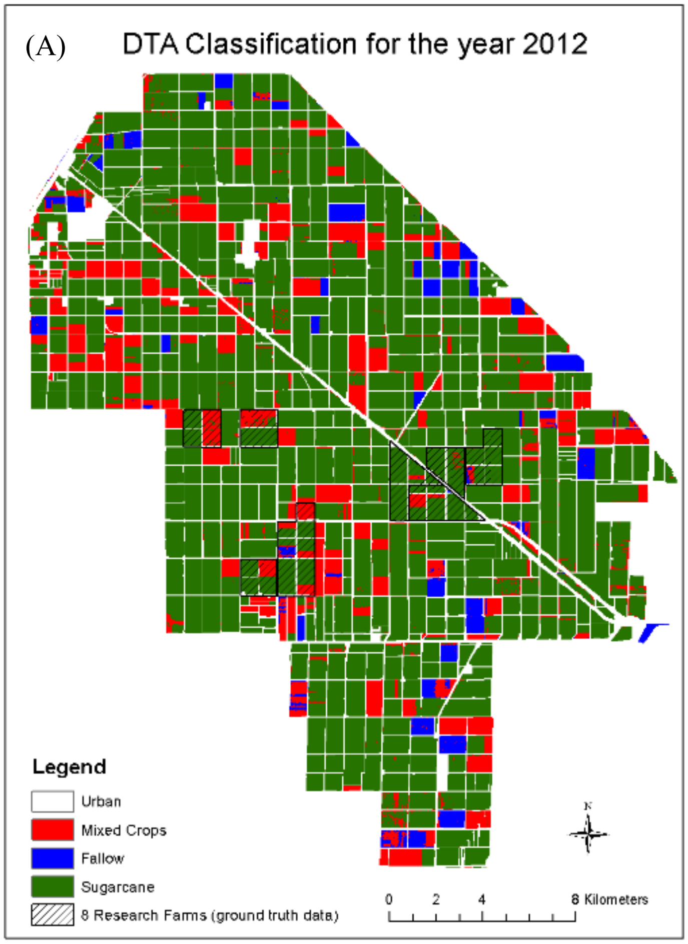


Figure 13- Classification results using the DTA methodology for the years 2012 (A), 2013 (B) and 2014 (C) in the S5A sub-basin.

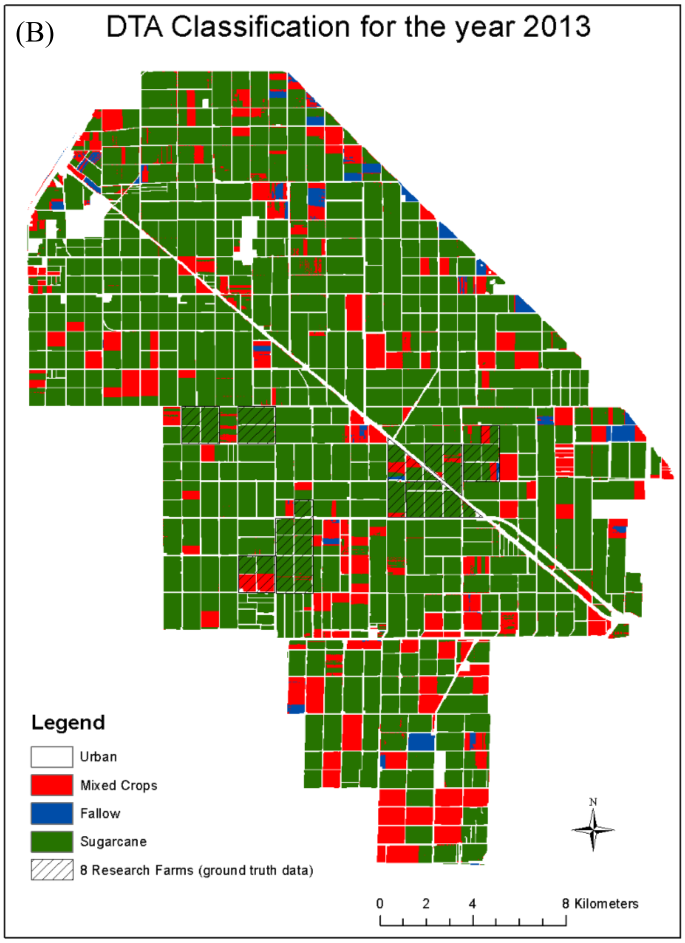


Figure 13- Continued.

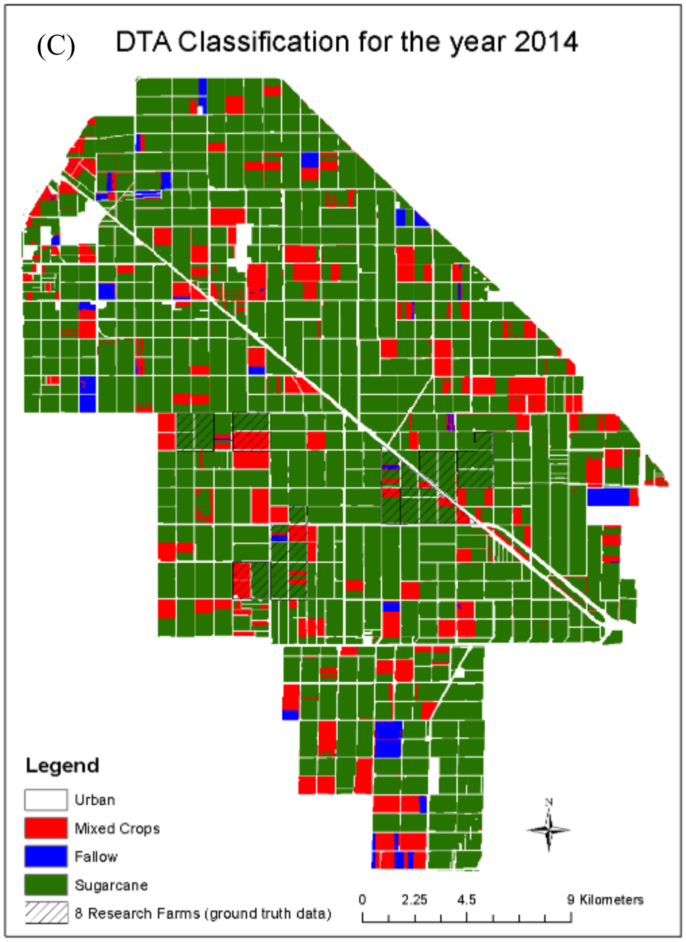


Figure 13-Continued.

Figure 14A, Figure 14B and Figure 14C illustrate the ANN classification results for the years 2012, 2013 and 2014 based on the random training of pixels for the three classes of information. The value of the classification is dependent on a range of issues, but most notably on its accuracy (Foody and Cox, 1994). Therefore, the confusion matrix (Foody,

2002) has been generated based on three years of reference data for the DTA and ANN classifications.

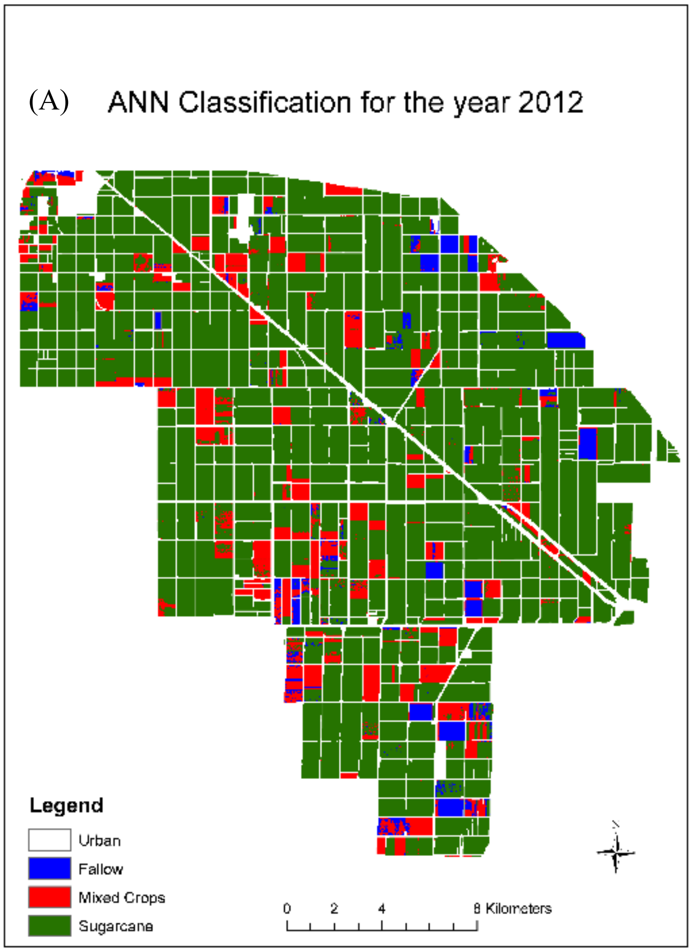


Figure 14- Classification results using the ANN methodology for the years 2012 (A), 2013 (B) and 2014 (C) in the S5A sub-basin.

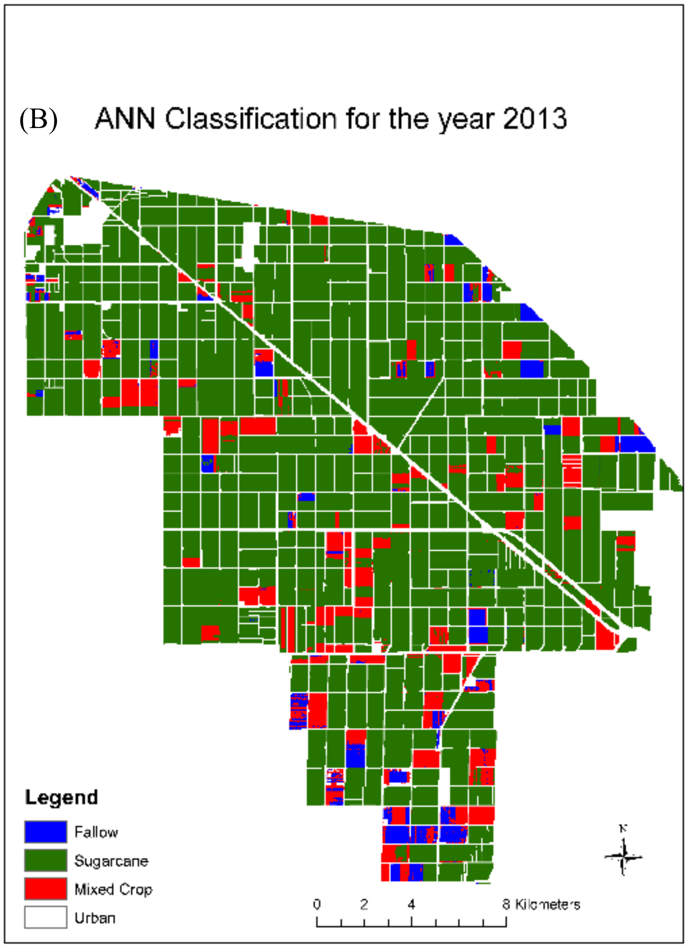


Figure 14- Continued.

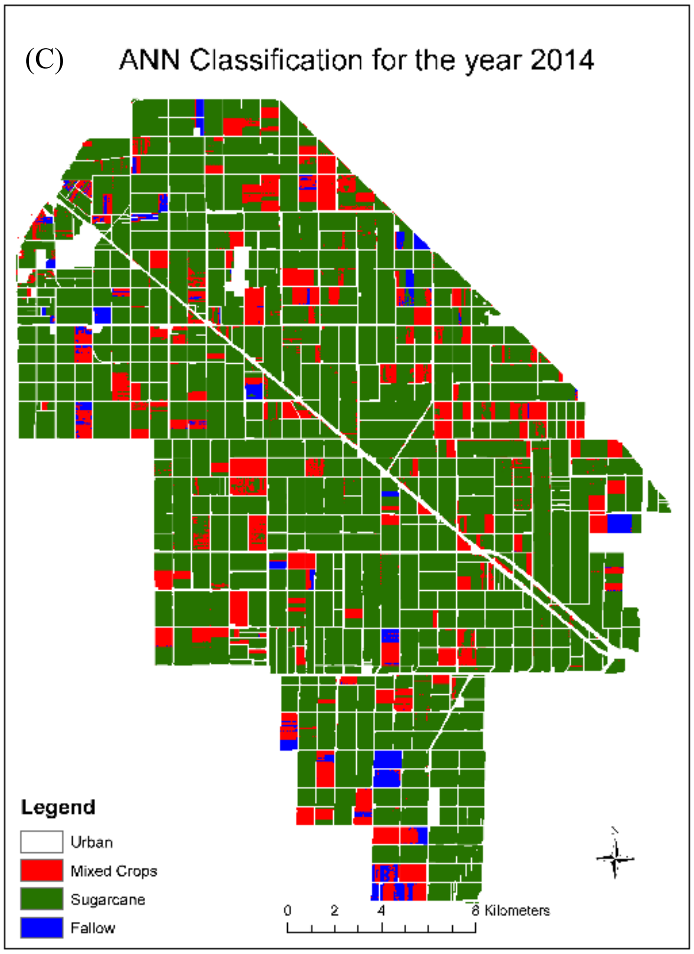


Figure 14- Continued.

The results are presented in Table 8 and Table 9, respectively. The confusion matrix was calculated by comparing the location and class of each ground truth pixel with the corresponding location and class in the classification image (Jansen, 1986). The overall accuracy is calculated by determining the number of correctly classified pixels and dividing by the total number of pixels. The kappa coefficient was used to measure the agreement between classification and ground truth pixels (Jansen, 1986). Landis and Koch (1977) suggested that a kappa coefficient greater than 0.81 is almost perfect. Using the DTA methodology, the classification led to three thematic maps with overall accuracies and kappa coefficients of 93.5% and 0.80 for the year 2012, 94.9% and 0.78 for the year 2013, and 97.9% and 0.93 for the year 2014 (Table 8).

Table 8- Confusion matrices for the maps generated using the DTA methodology and based on 25,479, 25,515 and 25,483 sampled reference pixels for the years 2012, 2013 and 2014, respectively.

Year 2012	Reference Map (%)	Overall Accuracy 93.5% Kappa Coefficient 0.79, CI [0.78 0.80] (P-value < 0.0001)			
	Classes	Fallow	Mixed Crops	Sugarcane	Total
	Fallow	76.1	7.3	0	1.6
DTA	Mixed Crops	23.9	90.0	5.6	20.0
	Sugarcane	0	2.7	94.4	78.3
Year 2013	Reference Map (%)	Overall Accuracy 94.9% Kappa Coefficient 0.78, CI [0.77 0.79] (P-value < 0.0001)			
	Classes	Fallow	Mixed Crops	Sugarcane	Total
	Fallow	100	3.7	0	0.8
DTA	Mixed Crops	0	88.3	3.4	11.3
	Sugarcane	0	7.9	96.6	87.9
Year 2014	Reference Map (%)	Overall Accuracy 97.9% Kappa Coefficient 0.93 CI [0.92 0.94] (P-value < 0.0001)			
	Classes	Fallow	Mixed Crops	Sugarcane	Total
	Fallow	69.6	0	0	1.3
DTA	Mixed Crops	30.4	99.3	1.7	18.4
	Sugarcane	0	0.7	98.3	80.4

Table 9- Confusion matrices for the maps generated using the ANN methodology and based on 12,739, 15,429 and 9,107 sampled reference pixels for the years 2012, 2013, and 2014, respectively.

Year 2012	Reference Map (%)	Overall accuracy 95.5% Kappa coefficient 0.83, CI [0.82 0.85] (P-value < 0.0001)			
	Classes	Fallow	Mixed Crops	Sugarcane	Total
	Fallow	83.1	4.6	0.2	1.3
ANN	Mixed Crops	16.9	95.1	4.6	18.7
	Sugarcane	0.0	0.4	95.2	80.0
Year 2013	Reference Map (%)	Overall accuracy 95.3% Kappa coefficient 0.75, CI [0.72 0.77] (P-value < 0.0001)			
	Classes	Fallow	Mixed Crops	Sugarcane	Total
	Fallow	12.9	0.3	0.1	0.2
ANN	Mixed Crops	87.1	92.3	3.8	11.3
	Sugarcane	0	7.4	96.1	88.5
Year 2014	Reference Map (%)	Overall accuracy 98.6% Kappa coefficient 0.95, CI [0.95 0.96] (P-value < 0.0001)			
	Classes	Fallow	Mixed Crops	Sugarcane	Total
	Fallow	94.3	0	0	2.0
ANN	Mixed Crops	5.7	99.8	1.5	18.4
	Sugarcane	0	0.2	98.5	79.6

Using the ANN methodology, the classification led to three thematic maps with overall accuracies and kappa coefficients of 95.5% and 0.83 for the year 2012, 95.4% and 0.75 for the year 2013, and 98.6% and 0.93 for the year 2014, respectively (Table 9). Confidence intervals around the sample estimate of kappa were constructed using the standard error of kappa and a Z score corresponding to a 95% confidence level, and its significance has been statistically confirmed by a Z test for the level of significance adopted (α = 5%). The user and producer accuracies, two widely used measures of classification accuracy, are presented in Table 10. The producer accuracy refers to the probability that a certain class is classified as such, while the user accuracy refers to the probability that a pixel labeled as a certain class in the map actually belongs to that class (Story and Congalton, 1986).

Table 10 - User and producer accuracies for the DTA and ANN methodologies.

	Classes	Fallow	Mixed Crops	Sugarcane
DTA 2012	Producer Accuracy	76.1	90.0	94.4
	User Accuracy	24.3	76.4	99.4
DTA 2013	Producer Accuracy	100	88.3	96.6
	User Accuracy	57.0	72.4	99.2
DTA 2014	Producer Accuracy	69.6	99.3	98.3
	User Accuracy	100	89.4	99.8
ANN 2012	Producer Accuracy	83.1	95.1	95.2
	User Accuracy	35.5	78.7	99.9
ANN 2013	Producer Accuracy	12.9	92.2	96.1
	User Accuracy	30.8	66.4	99.3
ANN 2014	Producer Accuracy	94.3	99.8	98.4
	User Accuracy	100	92.7	99.5

3.4 Discussion

DTA generated classes of information based on human interaction in the construction of the knowledge model. It had the potential to generate more sub-classes, while the ANN analysis produced classes of information in a supervised manner. For DTA, it was assumed that the NDVI patterns for sugarcane, fallow fields and mixed crops that were identified based on the NDVI time series from the year 2011 were also applicable to the years 2012, 2013 and 2014. Further classification of sugarcane into more specific classes, such as early-harvested and late-planted sugarcane, could be accomplished by incorporating knowledge of the phenological behavior of each specific class into the DTA. In the Figure 14A and Figure 14B , the ANN classification maps for the years 2012 and 2013 are limited to the study area within the scene located at WRS-2 path 15, row 42, because there were no training data available for the scene located at WRS-2 path 15, row 41. The DTA coverage is complete because the pattern recognition abilities of DTA are easy to transfer from one scene to another, while the pattern recognition abilities derived using ANN are difficult to transfer. This implies that DTA is more transparent, reproducible, and of greater utility when compared with ANN. Overall, the DTA and ANN classifiers showed consistent patterns with regard to the classification of the sugarcane, mixed crops, and fallow classes (Figure 13 and Figure 14). Moreover, the overall accuracies of the DTA-derived classification maps were above 90%, which can be considered successful crop identification. However, considering the proportion of ground truth pixels used in both the DTA and ANN approaches, DTA performed better and used fewer resources. The kappa coefficients were 0.93 and 0.96 for the year 2014 for the DTA and ANN approaches, respectively, representing almost perfect agreement, while the kappa coefficients for the years 2012 and 2013 represent substantial agreement. The year 2013 showed the least favorable kappa coefficients of 0.78 and 0.75 for both the DTA and ANN approaches. One reason why the largest and smallest accuracies appeared in the years 2013 and 2014 could be the number of NDVI bands in each composite image; 7 bands were available for the year 2012, 6 bands were available for the year 2013, and 8 bands were available for the year 2014. Therefore as the database size decreases, the classification accuracy also declines. It is also worth mentioning that the composite images covering the years 2012 and 2013 were mainly made from Landsat-7 images, while the composite image covering the year 2014 was made from Landsat-8 images. The latter instrument is enhanced compared to prior Landsat instruments in terms of data quality and radiometric quantization. The kappa values indicate the good quality of the thematic maps generated. According to the confusion matrix, stronger confusion occurred between mixed crops and fallow regions (DTA: 24% for the year 2012 and 30% for the year 2014; ANN: 16.9% for the year 2012, 87.1% for the year 2013 and 5.7% for the year 2014). Regarding the descriptive statistics, my main interest was whether the reference data were correctly classified (producer accuracy), not whether the classified data contained the correct data (user accuracy) (Story and Congalton, 1986). As such, the results for both the DTA and ANN approaches for sugarcane and mixed crops reflected high producer accuracies, while fallow regions had large to small producer accuracies. The relatively small number of ground truth fallow pixels used for the purposes of training and reference could explain this: 134 such pixels were available for the year 2012, whereas 117 and 460 such pixels were available for the years 2013 and 2014, respectively. The number of ground truth pixels for sugarcane were 21,002 for the year 2012, 23,039 for the year 2013, and 20,807 for the year 2014, and the corresponding numbers for the mixed crops class are 4,343 pixels for the year 2012, 2,360 pixels for the year

2013, and 4,216 pixels for the year 2014. As the availability of high quality ground truth data increases, the performance of supervised algorithms exhibit corresponding improvements (Friedl and Brodley, 1997). This again highlights the limitations of supervised classification in terms of the availability of ground truth data for every single classification.

3.5 Conclusion

A methodology was developed to classify sugarcane using repetitive and moderate spatial resolution data from Earth-observing satellites, such as Landsat. The power of DTA was utilized to perform crop mapping using multi-temporal satellite-derived NDVI composite images. Using the ANN and DTA approaches, the NDVI temporal profile was successful in discriminating sugarcane from other crops and fallow fields. In terms of overall accuracy and kappa coefficients, the overall performances of the ANN and DTA approaches were similar, whereas DTA showed advantages in terms of its producer accuracy and ability to produce more classes of information. The results of the accuracy assessment showed that for both methods, the accuracy increases with increase in the number of the NDVI bands and also the quality of the data. DTA showed significant potential for discrimination of sugarcane from other crops without demanding ground truth data for every year. The unique strength of DTA lies in its flexibility and simplicity; it has the further advantage of being nonparametric and therefore makes no assumptions regarding the distribution of input data. The results strongly suggest that DTA provides an excellent opportunity to expand knowledge of land use dynamics in agricultural areas, which is a critical function of environmental and land management programs used worldwide by government, industry, and non-governmental sectors.

4. ENVIRONMENTAL AND MANAGEMENT CONTROLING PHOSPHORUS LOADING IN THE EVERGLADES AGRICULTURAL AREA

4.1 Introduction

The EAA basin consists of primarily organic soils subjected to mainly sugarcane and vegetable cropping for approximately 100 years (Aich et al., 2013). P deficiency caused by inherently low concentrations of available P in the EAA soils is the main biophysical constraint to sugarcane production. The soils of the EAA are characterized by a high P adsorption capacity and thus a large proportion of total P is converted to P forms, which are not available to plants (Bottcher and Izuno, 1994). To ameliorate low available soil P, application of P fertilizer on the EAA soil has made the system economically viable but ecologically questionable. P management requirements in agro-ecosystem must be managed to ensure adequate P availability for optimum crop production and to minimize losses of P in runoff (Bundy et al., 2005). P availability is governed by complex dynamics of P in soil which in turn is affected by numerous factors including site-specific variables such as farm size, soil type , land use practices, cropping system, and strategy of P management such as type of fertilizer applied, the rate and method of application, farm water management and P concentration in irrigation water (Singh et al., 2005, Withers et al., 2005, Daroub et al., 2009, Grunwald et al., 2009, Lang et al., 2010, Rice and Izuno, 1996).

Major advances in understanding of P BMPs for agricultural production have been observed due to the two-sided challenge of P sustainability (pollution on one hand and scarcity on the other) (Pierzynski et al., 2005, Elser, 2012). As such, scientists, land managers, and regulatory agencies have worked with the agricultural community in the EAA to develop improved approaches to P management. Since 1973, water quality has been monitored at discharge points leaving the EAA to the north and south (SFWMD, 1986) and "on-farm" conservation programs have been implemented to reduce P concentration in drainage water leaving the EAA since 1995 (Rice et al., 2013). Unfortunately little water quality monitoring has been done on farms in the EAA to study the processes that may control the transport of P from soils to surface water bodies. Due to limitations associated with monitoring, these studies (Rice et al., 2002, Daroub et al., 2011, Stuck et al., 2001) were conducted at few specific research farms and did not account for heterogeneity of farms in the basin. Despite these research findings, understanding of how farms with different management, land use and site specific variables and BMP types affect P loads is still limited. Ongoing studies and information are needed to ensure that the management practices adopted are the most appropriate and cost effective to maintain a healthy balance between good agriculture and good water quality.

By integrating remote sensing, GIS and multivariate statistics, the effects of varying BMPs, land use and farm characteristics on the P load in farm runoff in the EAA basin are examined in this paper at a broad scale, addressing two major research questions: (1) What are the static, slow transient and fast transient environmental factors affecting P loads in farm runoff in the EAA basin (2) Does the effect of BMPs on P load vary predictably between seasons and can a dominant mechanism controlling these dynamics be identified? Thus, the goal of this study is to provide critical and scientific information needed for EAA management decisions. This study is unique to the EAA in that it combines several key aspects: an extensive spatial coverage (48,324 ha), an extensive temporal coverage (5 consecutive years 2010-2014) and a fine temporal resolution which permit multivariate analysis and quantitative statements about the impact of BMP types on P loading in EAA runoff. The multivariate analysis was used in order to better understand interrelationships among P load, BMPs, rain and land use. This study contributes to documenting the effectiveness of P control efforts and provides information on several factors affecting the success of BMPs in the EAA.

4.2 Methods

4.2.1 Study Area

Our study focused on S5A sub-basin (48,324 ha) of the EAA basin (Figure 15) comprising approximately 280,000 ha of flat landscape south of Lake Okeechobee and north of three water conservations areas (WCAs). Complex mosaics of vegetative habitats interspersed on the flat peat bed historically covered this region but over the past century, the EAA has been drained and converted to agricultural land use (Voss, 2000). Although sugarcane is the dominant agriculture crop, the EAA also produces vegetables, rice, sod, and contains improved pastures. The EAA contains a surficial aquifer system consisting of rocks and sediments between the land surface and underlying limestone (Harvey and McCormick, 2009). Most of the soils in the EAA contain more than 70% soil organic matter (Histosols, suborder: Saprists) that is highly decomposed (Snyder, 1994). The Histosols of the EAA were formed over a 4,400 year period from partially decomposed remains of hydrophytic vegetation that accumulated under anaerobic wetland conditions (Snyder, 1994). Under the soil classification system (Soil Conservation Service, 1988), four series in the study area are recognized, in the order of decreasing soil thickness : Terra Ceia, Torry, Pahokee, and Okeelanta series (Rice et al., 2005, Snyder, 2005). Because of the extensive drainage and subsequent oxidation, these soils are subsiding at a rate of approximately 2.5 cm per year (Reddy et al., 1998). The characteristics of each soil series are listed in Table 11.

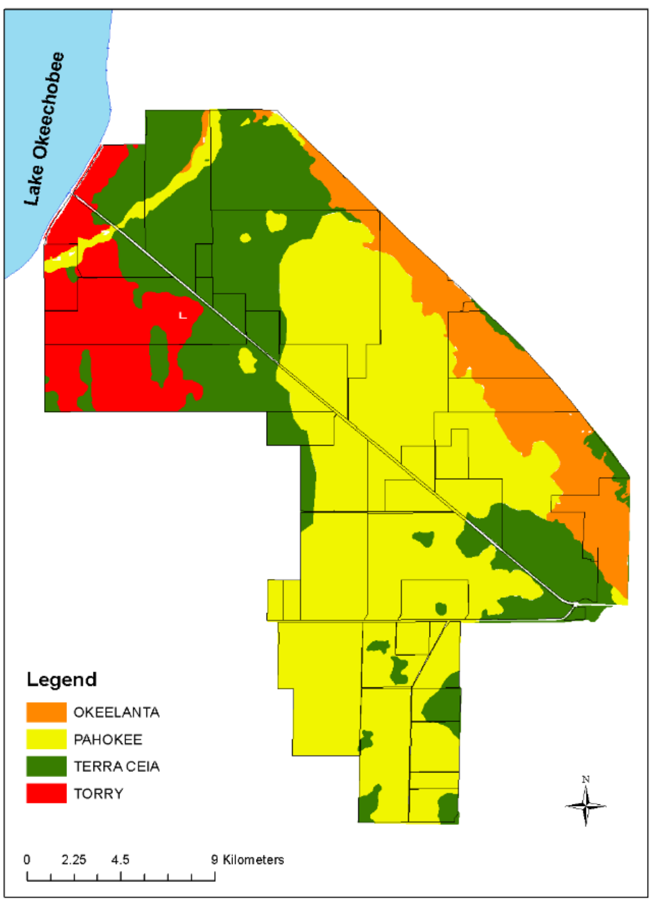


Figure 15- Soil series of the S5A sub-basin.

Table 11- Properties of soil series found in the S5A sub-basin (California Soil Resource Lab, 2016)

Soil Series	% Organic matter	Mineral content %	Thickness of organic material (cm)	Underlying material	Saturated hydraulic conductivity (mm hr^{-1})	Cationic exchange capacity at pH 7 Cmol charge kg soil	Soil bulk density g cm^{-3}
OKEELANTA	75	<35	41-127	Sand	331.2	124.4	0.25
PAHOKEE	82.5	<35	91-130	Limestone	331.2	156	0.25
TERRA CEIA	72.5	<35	>130	Limestone	331.2	121.2	0.25
TORRY	35	>35	>130	Limestone	331.2	99.8	0.25

4.2.1.1 BMPS Implemented in the EAA

Heightened concerns about the impact of drainage waters from the EAA into the Everglades ecosystem urged the South Florida Water Management District (SFWMD) to design and install Stormwater Treatment Areas (STAs) and to develop and implement a best management practice regulatory program (EAA BMP rule) (Fumero and Rizzardi, 2011). The BMP rule requires all farmers in the EAA basin implement farming practices to reduce the P discharge from their properties to an environmentally acceptable level at the SFWMD pump stations along the southern border of the EAA while simultaneously maintaining an economically viable farming operation for the grower (Daroub et al., 2011). Monitoring of daily farm drainage volumes and P concentrations began in July 1992.

Farmers in the EAA are required to adopt a minimum of 25 points of BMPs with assigned SFWMD points (Daroub et al., 2005). BMPs are designed to reduce P loading by either managing the volume of discharge water or reducing P concentration in discharge water by using sediment and nutrient control practices (Izuno et al., 1995). Maintaining the water level elevation is an important hydrological practice to control the farm P load in the runoff (Abtew and Khanal, 1994). It is also a key factor to optimize the agricultural yield and to control the soil subsidence and the soil oxidation rate (Reddy and DeLaune, 2008). The farmers in the EAA generally adopt similar BMPs while varying the rainfall detention amount (12.7 or 25.4 mm) before drainage pumping is initiated and the number of implemented particulate matter and sediment control practices. Particulate matter and sediment control BMPs focus on both minimizing the transport of sediments off the farm and removing accumulated sediments from canals (Daroub et al., 2005). Examples of sediment BMPs include laser leveling of fields, constructing ditch and canal sumps to trap sediments, low water drainage velocity in the canal, and a canal cleaning program (Daroub et al., 2009). Two types of BMP, WM5 (Water Management 5 points) and WM10 (Water Management 10 points), each having the required 25 points were found in the study area (Table 12). The BMP type WM5 has 5 points of water management practices and BMP type WM10 has 10 points of water management practices. Adopting 4 practices of sediment controls will count for 5 points and adoption of 6 practices will count for 10 points. A map representing the implemented BMP type for each farm in the S5A sub-Basin for the years 2010-2011 is shown in Figure 16A and for the years 2012 through 2014 is shown in Figure 16B. Despite BMP implementation, an important farm P load variability is generally reported within each sub-basin (SFWMD, 2008).

Table 12- Two main BMP types implemented in the EAA (Daroub et al., 2014).

BMP Type	Nutrient Control Practices		Water Management Practices		Particulate Matter and Sediment Controls	
WM5	Nutrient application control Nutrient spill prevention and soil testing	10 pts	Rainfall detention amount 12.7 mm	5 pts	min of 6 practices required	10 pts
WM10	Nutrient application control Nutrient spill prevention and soil testing	10 pts	Rainfall detention amount 25.4 mm	10 pts	min of 4 practices required	5 pts

(A) (B)

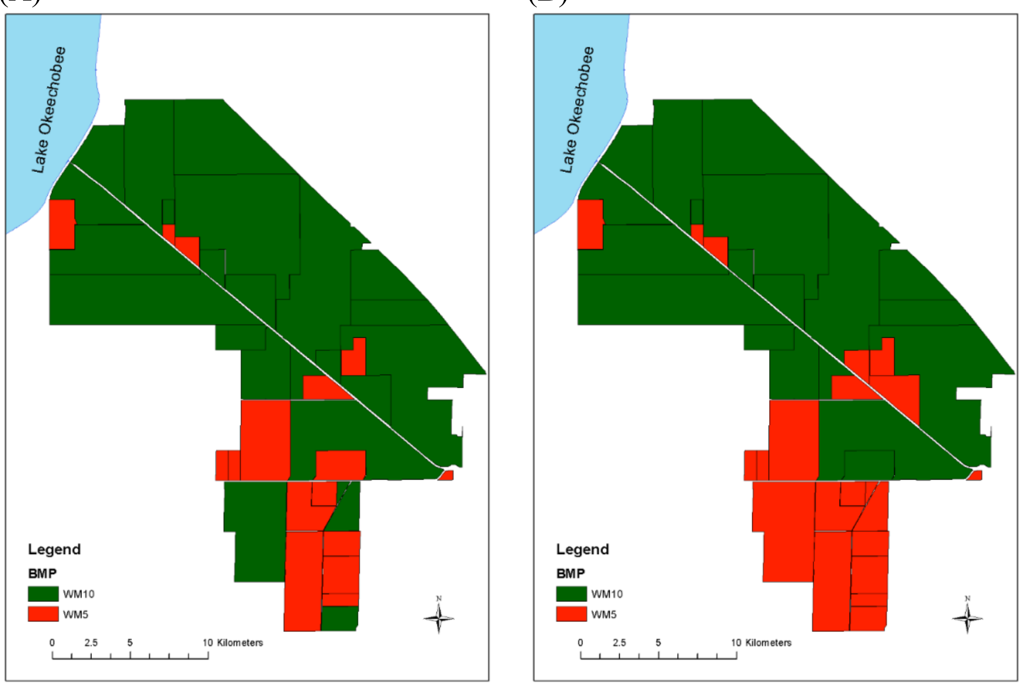


Figure 16- BMP types implemented in the S5A sub-basin for the years 2010-2011 (A) and for the years 2012-2014 (B). BMP type: rainfall detention of 25.4 mm [WM10] and rainfall detention of 12.7 mm [WM5]. WM stands for Water Management.

4.2.1.2 Land-Use Classification

Sugarcane planting takes place from late August through January. Typically, a sugarcane field is replanted every two to four years. After a field has been harvested the first time, a second crop of stalks, called a ratoon, grows from the old plant stubble. The second crop is harvested about one year after the first harvest (Baucum et al., 2006). On average, three annual crops are harvested from one field before the field is replanted. When annual production declines to an unacceptable level, the old sugarcane crop is plowed under after harvest, and the land is prepared for replanting with new seed cane (termed "successive planting"), the field may also be planted using another crop such as vegetables, row crops, rice or sweet corn (termed, "fallow planting" or "mixed crop"), or may be kept fallow. Sugarcane is generally harvested from late-October through mid-April. Given no damaging effects from freezing conditions, sugar yields are typically highest after December (Baucum et al., 2006). After three or four years of successive sugarcane harvest, the sugarcane area can also include fallow or fallow planting.

The four classes of land-use namely: "sugarcane", "mixed crop", "fallow" and "urban area" were defined in the study area with the overall accuracy of 94% following the methodology in the previous section. This land-use classification (sugarcane, mixed crop, fallow or urban areas) is reported in percentages indicating the area of each farm under a specific classification for five consecutive years from 2010 to 2014.

4.2.1.3 Seasonality

Only two seasons exist in south Florida: wet (five-month rainy season from June through October) and dry (seven-month dry season from November through May). Large quantities of water are pumped into the fields during the dry season and are drained from the fields during the wet season.

4.2.2 Statistical Analysis of P Load as Affected by Environmental Factors

Multivariate analyses were conducted using the following environmental variables for each farm in the S5A sub-basin: (1) BMP type : rainfall detention of 25.4 mm [WM10] or rainfall detention of 12.7 mm[WM5], (2) Monthly total P load per unit area (kg ha^{-1} $month^{-1}$) [ULA], (3) Sugarcane cover (%) [Sugarcane], (4) Mixed vegetation cover (%) [Mixed], (5) Fallow cover (%) [Fallow], (6) Okeelanta soil cover (%) [OKEELANTA], (7) Pahokee soil cover (%) [PAHOKEE], (8) Terra Ceia soil cover (%) [TERRA CEIA], (9) Torry soil cover (%) [TORRY], (10) Monthly rainfall (cm $month^{-1}$) [rain], (11) rainfall with one month lag (cm $month^{-1}$) [antecedent rainfall], (12) Distant to outlet (km) [DO], (13) Farm Perimeter (km)[PR], (14) Season [Wet/Dry]. The average rainfall in the EAA is approximately 122 cm yr^{-1} and therefore year 2011 with 116.87 cm yr^{-1} of rainfall was considered a dry year and year 2013 with 127.03 cm yr^{-1} of rainfall was considered a wet year. Monthly rainfall distribution of years 2010 through 2014 is shown in Figure 17.

The data matrices were first checked for outliers before starting the analysis because multivariate techniques are sensitive to outliers (Shaw, 2009). The following months were removed from the data set because no or very little rainfall occurred during these months: Year 2010 - October and November; Year 2011 - May; Year 2012 - June and November; Year 2013 - January, November and October; Year 2014 - December. The seasonal variations in log ULA on a monthly basis for five consecutive years are presented in Figure 18. Each variable distribution was checked for normality and a transformation was applied if necessary to control the data distribution. Since the distribution of log ULA had a consistently similar seasonal pattern (Figure 17 and Figure 18), I hypothesized that rainfall is impacting the release of P from farm runoff.

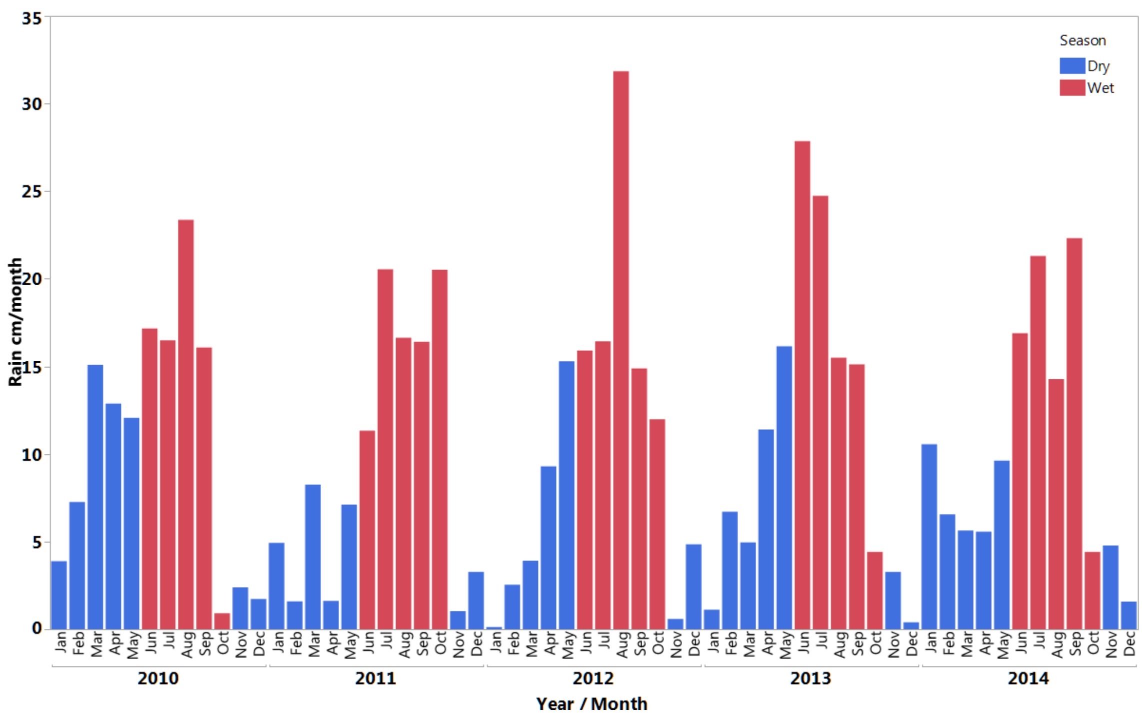


Figure 17- Monthly rainfall distribution for years 2010-2014.

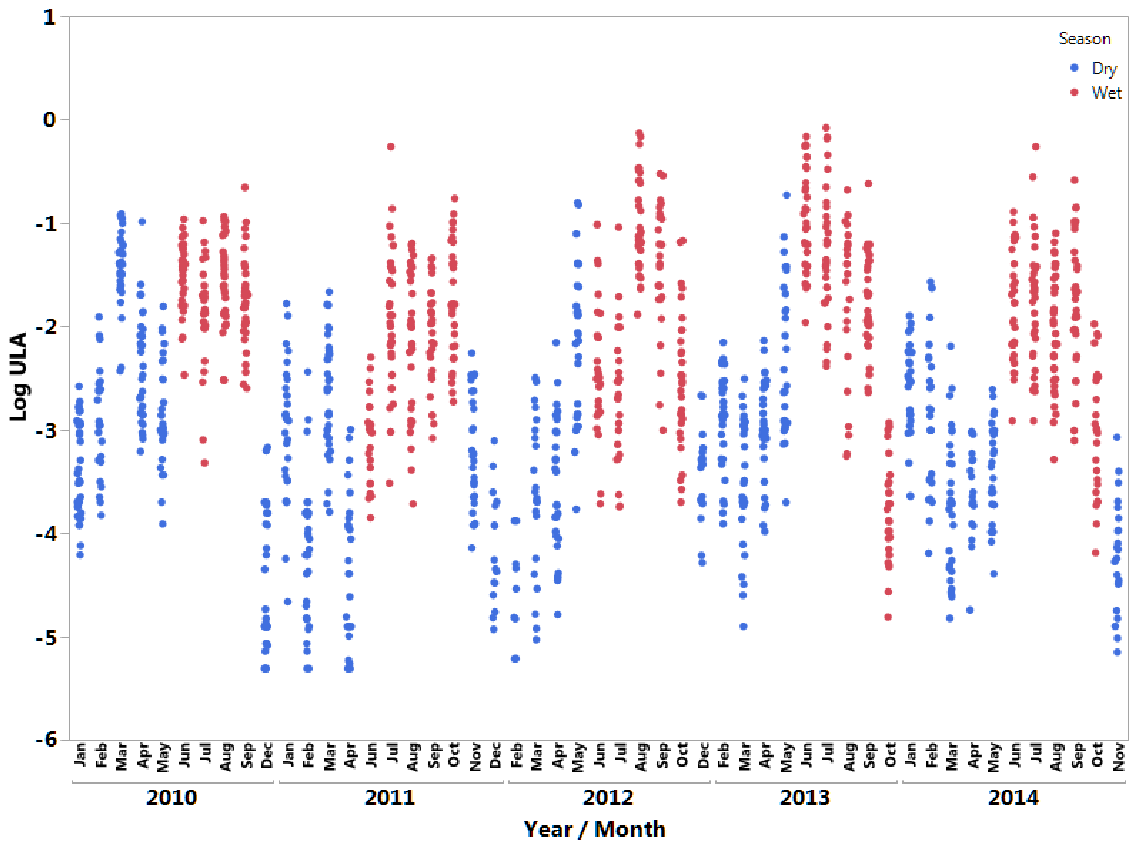


Figure 18- Seasonal changes in mean log ULA in the S5A sub-basin for the years 2010-2014.

4.2.2.1 Principal Component Analysis

A Principle Component Analysis (PCA) was conducted to seek visual evidence of informative pattern in the data. It involved treating the set of data as a geometrical object, then finding the most informative angle from which to view the shape (Shaw, 2009). The principal axis score can be handled in the same way as primary (i.e. measured) variables. In addition to being plotted, data can be subjected to rigorous inferential statistics such as regression analysis or analysis of variance.

4.2.2.2 Partition Analysis

A partition analysis was performed between log ULA (as response) and rain and BMP type as factors to find the cut value that best predicted the log ULA variability. The partition analysis recursively partitions data according to the relationship between a response and factors (Richardson and Clarke, 1985). It does this by exhaustively searching all possible splits (or partitions) of factors that best describe a response and then chooses the optimum splits from a large number of possible splits.

4.2.2.3 Correlation and Regression Analysis

Prior to analysis, several variables were transformed to meet the conditions of normality. Monthly total P load per unit area was log transformed. All land-cover percentages were square root transformed. Other variables used in the regression analysis did not require any transformation.

Pearson's correlation was applied to test for potential spatial correlation of my data set. Sugarcane percentages were significantly correlated with the Mixed (*r* values were -0.63 (year 2010), -0.81 (year 2011), -0.72 (year 2012), -0.45 (year 2013) and -0.72 (year 2014)), the PAHOKEE was correlated with the TERRA CEIA (*r* value -0.81) and DO was correlated with the PAHOKEE (*r* value -0.71), TERRA CEIA (*r* value 0.65) and Urban (*r* value 0.58). The rest of the variables showed *r* values less than 0.2 during the months examined in this study and were accepted as independent.

PCA and univariate linear regressions initially were used to assess relationships between log ULA and individual explanatory variables. Stepwise backward multiple regressions were subsequently performed to model the monthly relationships between log

ULA and explanatory variables in the study area. To avoid collinearity between variables within my models, the number of variables included in the models was reduced using the variance inflation factor (VIF). VIF measures how much the variance of the estimated regression coefficients are inflated as compared to when the explanatory variables are not linearly related. A general rule is that the VIF should not exceed 10 (Belsley et al., 2005). The corrected Akaike's Information Criterion ($AICc$) was used as an information-based criterion to assess model fit. Variable selection in regression models should consider a call for a balance between models with too few variables (under fitted models) and with models having too many variables (over-fitted models) (Burnham and Anderson, 2004). Inference with under fitted models can be biased while over-fitted models provide poor identification of effects (Hurvich and Tsai, 1989). The minimum $AICc$ criterion produces a selected model which is close to the best possible choice (Hurvich and Tsai, 1989). At the outset of the regression analysis study, a hypothesis was formulated regarding the relationships between the variables of interest, e.g. log ULA and the explanatory variables including rainfall, antecedent rainfall, land-use, soil type, farm perimeter, BMP and rainfall threshold. Mean values and ranges for all the variables are listed in Table 13. The interpretation of the coefficient estimates in a multiple regression model $I = BX + \alpha$ is as follows: α captures what amount of log ULA an individual farm releases with no effect of explanatory variables and B captures the effect of explanatory variables. The resulting models created using these criteria had the minimum $AICc$, VIFs below 10 and produced acceptable plots of residuals. Validation was performed with 75% of the data serving as a training set and 25% of the data serving as validation. All statistical analyses were performed using SAS (SAS Institute, 2001).

Table 13- Mean values and ranges for the environmental parameters used for the multivariate analysis.

Parameter	Mean	Range	Code
log of unit load of total P per area [kg ha^{-1} $month^{-1}$]	-2.59	-6.00 ~ -0.08	log ULA
Rainfall [cm $month^{-1}$]	12.47	1.27 ~ 31.85	R
Antecedent rainfall [cm $month^{-1}$]	11.80	0.13 ~ 31.85	AR
BMP type			WM5- WM10
Soil type (% land cover)		0 ~ 100	OKEELANTA/PAHOKEE/TERRA CEIA/TORRY
Land use (% land cover) Urban Fallow Mixed vegetation Sugarcane		0 ~ 100	 UR FA MX SG
Perimeter [km]	14.75	4.03 ~ 44.00	PR
Distant of discharging point to the basin outlet [km]	13.47	0.29 ~ 27.73	DO
Rainfall threshold [cm $month^{-1}$]	13.25		R≥ 13.25 / R<13.25

4.3 Results and Discussion

This study sought to identify the independent variables that may be responsible for controlling unit loading of total P per area (ULA).

4.3.1 Preliminary Data Analyses

Descriptive statistics of the continuous variables were examined prior to conducting multiple regression analysis. A biplot provides visual examination of the relationship between the explanatory variable and the dependent variable.

4.3.1.1 Soil Series Effect on Log ULA

The plots of log ULA vs. soil series during dry and wet seasons are presented in Figure 19A through Figure 19H. These plots are color coded and follow the monthly rainfall rates. These plots demonstrate that the soil type did not have a strong relationship with log ULA. The insignificance role of the soil series in predicting log ULA lies in the fact that the Histosols of the EAA are classified in part by the depth to concentrated mineral matter (rock, sand) (Snyder, 2005), their physical and chemical properties such as texture, cation exchange capacity, bulk density, structure, porosity, pH , etc. are similar. Also the soils in the EAA like other agricultural areas have undergone erosion, ripping, land leveling and are drastically disturbed soils. Univariate regression analysis between log ULA and soil series were able to explain less than 10% of the variance in log ULA between sites for dry and wet seasons.

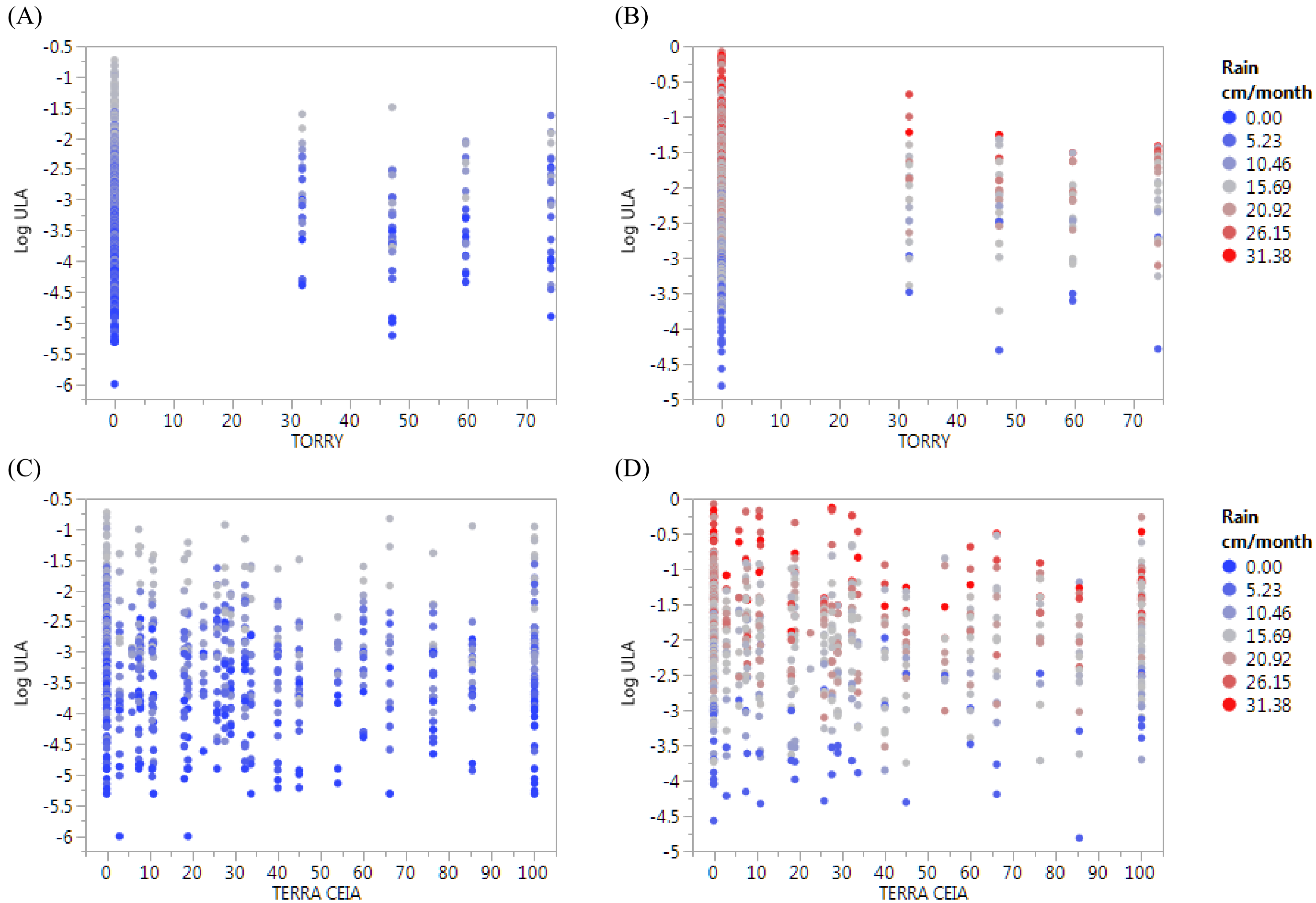


Figure 19- Plots of log ULA vs soil series TORRY, TERRA CEIA, PAHOKEE and OKEELANTA as % of land cover for all years and color coded by rainfall in cm/month (left columns during dry season and right columns during wet season).

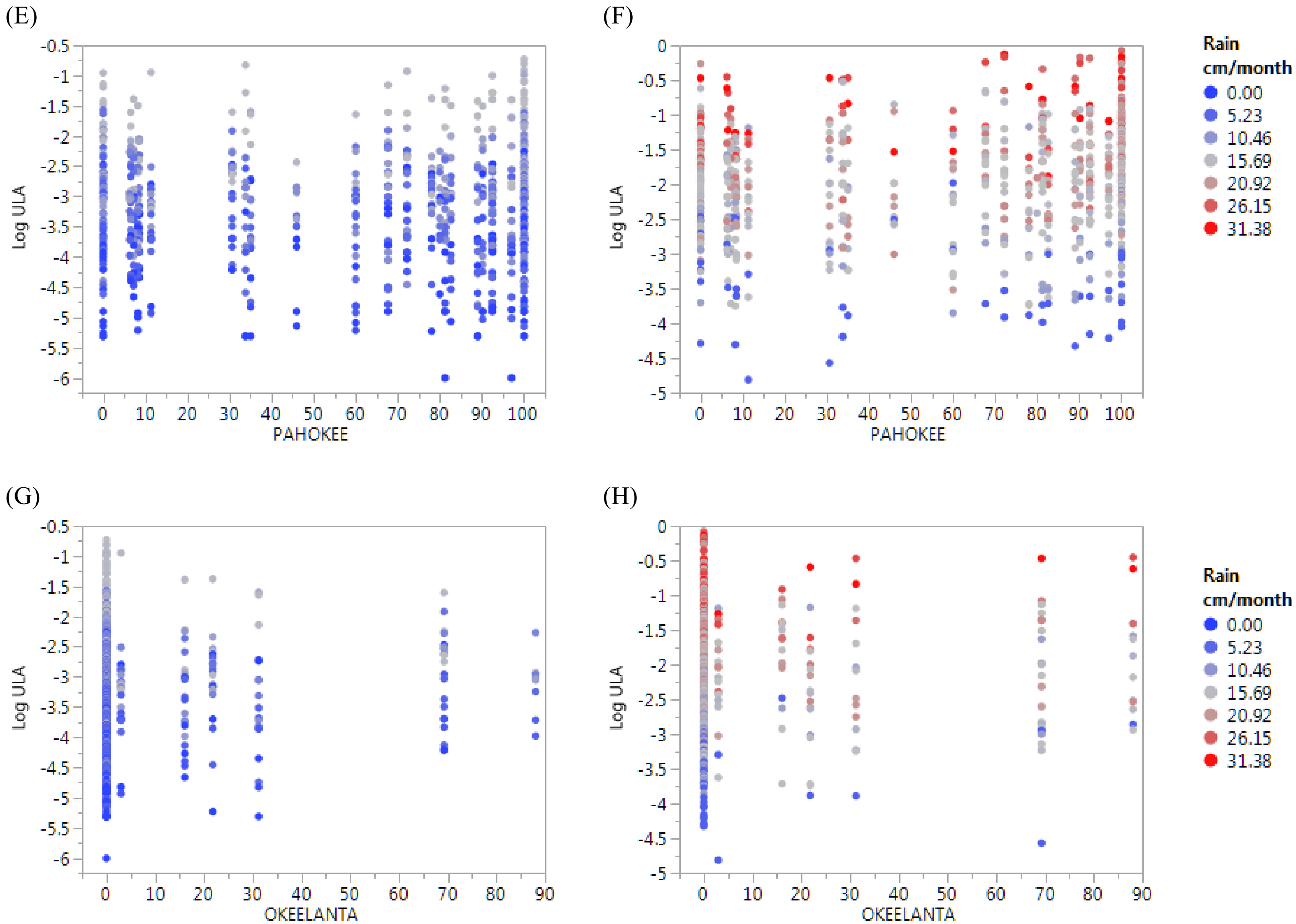


Figure 19- Continued.

4.3.1.2 Relationship Between Log ULA and Land Use

Land use types in the study area were sugarcane, fallow, mixed crops and urban area. The plots of land use vs. log ULA (Figure 20A through Figure 20H) indicate that a relationship exists between those two variables, thus a PCA analysis was performed allowing the visualization of multivariate information.

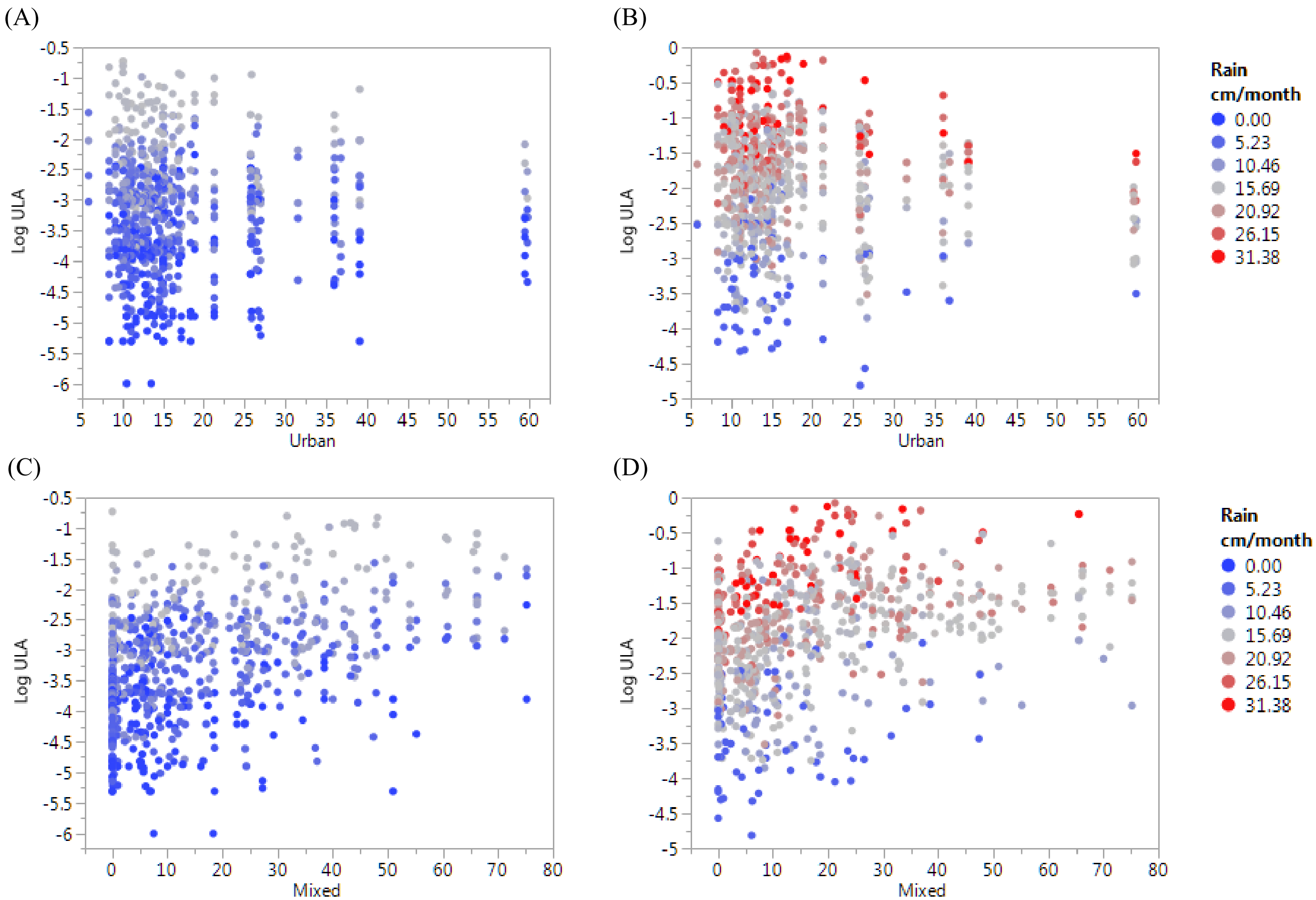


Figure 20- Plots of log ULA vs land-use types: Urban, Mixed, Fallow and Sugarcane as % of land cover for all years color coded by rain (cm/month) (left column during dry season and right column during wet season).

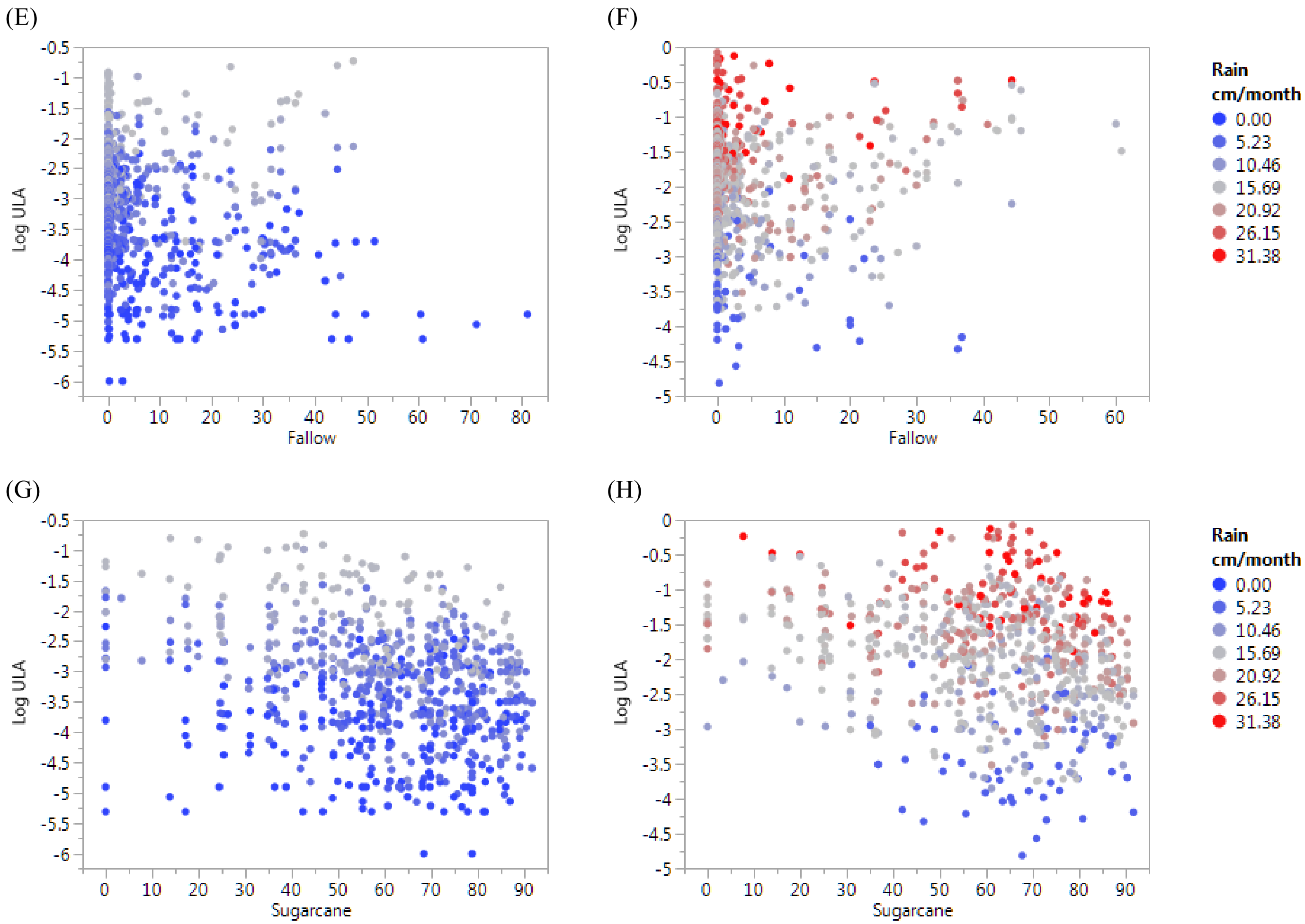


Figure 20- Continued.

The results are presented using biplot diagrams with the maximum variance projected along the first axis and the maximum variation (uncorrelated with axis one) projected on the second axis (Figure 21A through Figure 21L). The eigenvector loadings (representing the variances extracted from each axis and often conveniently expressed as a percentage of the sum of all eigenvalues (i.e. total variance)) are added as arrows to the plots. Figure 21 showed that the first axis had positive eigenvector loadings with mixed vegetation and negative eigenvector loadings with sugarcane. This can be interpreted as follows: The greatest source of variation is within the mixed vegetation and sugarcane. Therefore, the largest separation in the data was between sugarcane and mixed vegetation as demonstrated by their separation on the first axis. The second axis was associated with urban and fallow land use. The resulting ordination diagrams suggest that during the dry seasons, the majority of farms on the right side of the first axis had above average log ULA while this relationship is not evident for the wet seasons. This result suggests that during dry seasons, farms with a higher percentage of mixed vegetation, had a higher P load in their farm runoff.

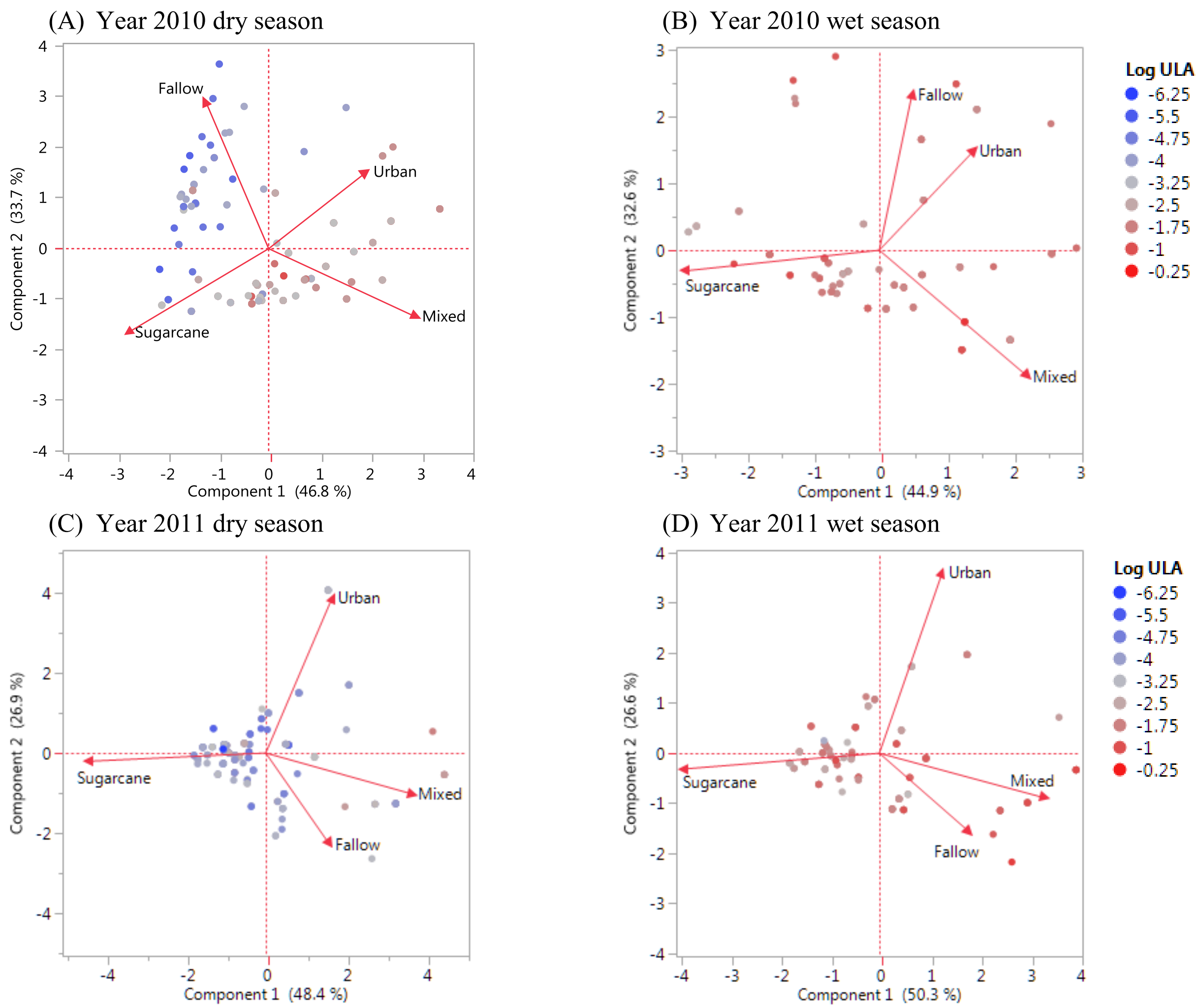


Figure 21- PCA ordination of the land-use superimposed with log ULA for dry and wet seasons during the years 2010-2014 (A) – (J) and for all combined years (K) and (L).

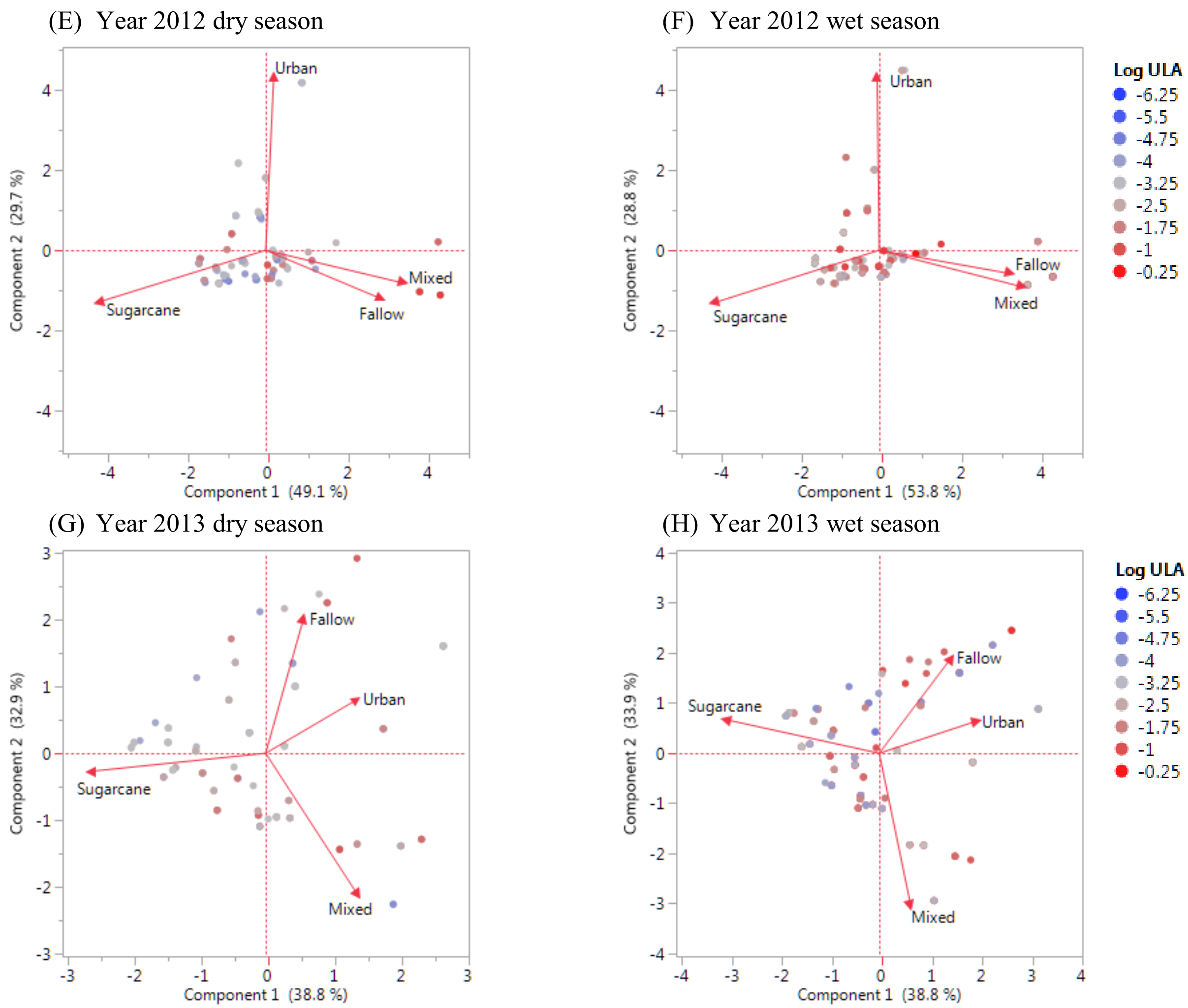


Figure 21- Continued.

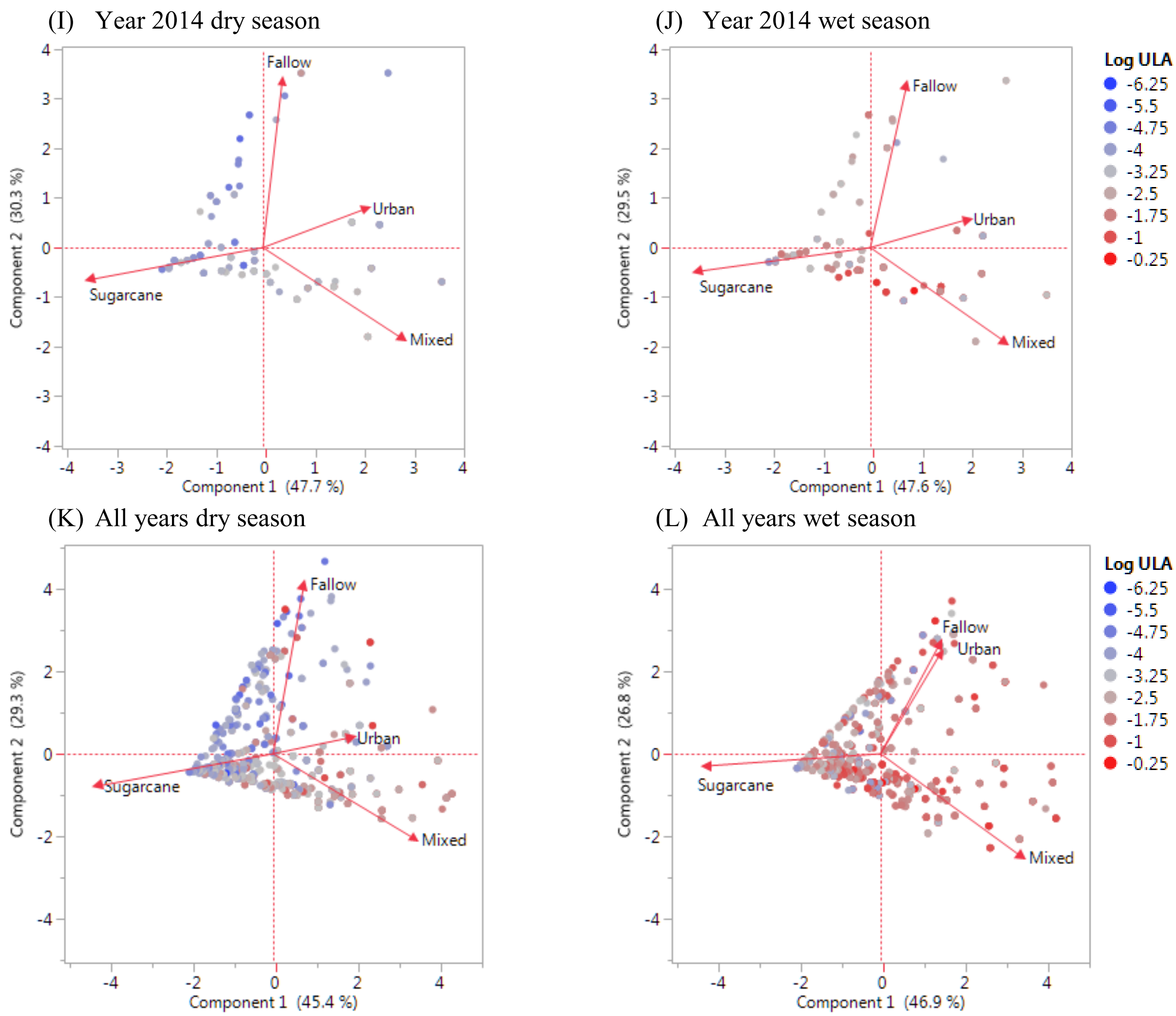
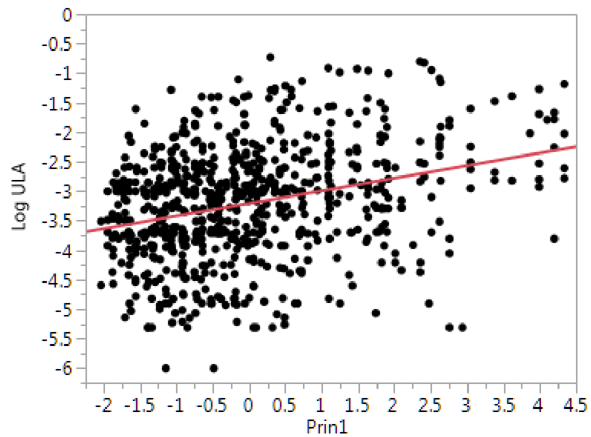


Figure 21- Continued.

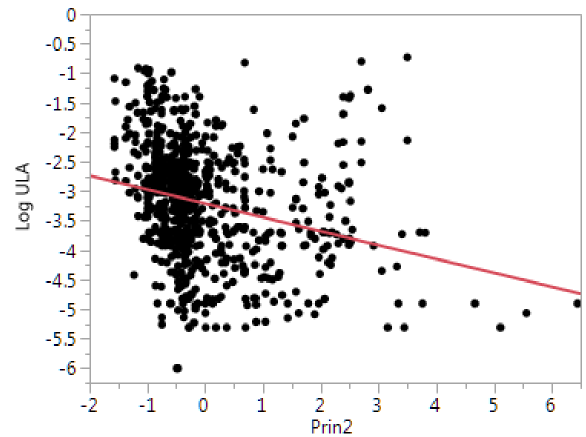
Analysis of variance on the PCA of all years showed a significant association between higher log ULA values and positive PCA scores for the first axis and lower log ULA values and positive PCA scores on the second axis at $\alpha = 0.001$ for both wet and dry seasons (Figure 22).

(A) PCA axis 1 vs log ULA for dry season



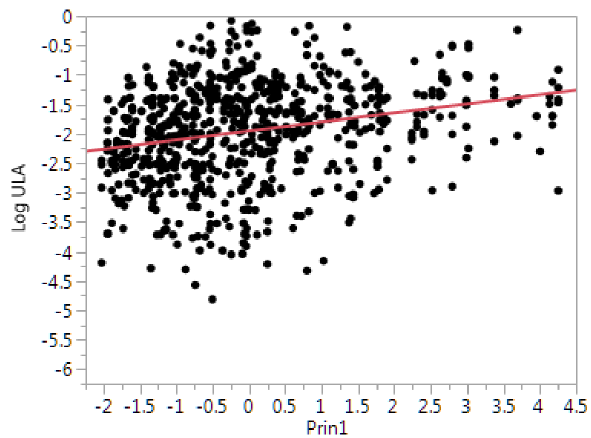
log ULA=-3.21+0.21xPrin1

(B) PCA axis 2 vs log ULA for dry season



log ULA=-3.21-0.23xPrin2

(C) PCA axis 1 vs log ULA for wet season



(D) PCA axis 2 vs log ULA for wet season

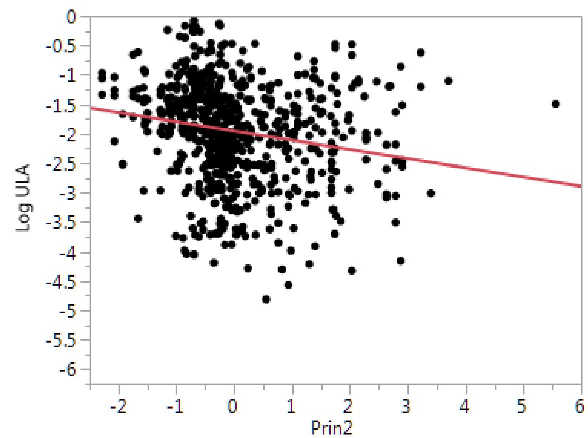


Figure 22- Plots of PCA axis 1 score (prin 1) and PCA axis 2 score (prin 2) vs log ULA for all years during dry and wet season.

During high rainfall events (storm events), farms associated with BMPs WM10 tended to have lower log ULA. On the other hand, during low rainfall events, farms associated with BMPs WM5 tended to have lower log ULA. The partition analysis is shown in Figure 23 presenting the plot of monthly log ULA vs. rain for two groups of farms with BMP WM10 and WM5. The rainfall threshold of 13.25±0.89 cm/month is the border of separation of BMP types with respect to their performance during high/low rainfall events. While several other factors could affect log ULA such as land use, this result indicated that the interaction of BMP and rainfall thresholds has to be included in the multivariate analysis.

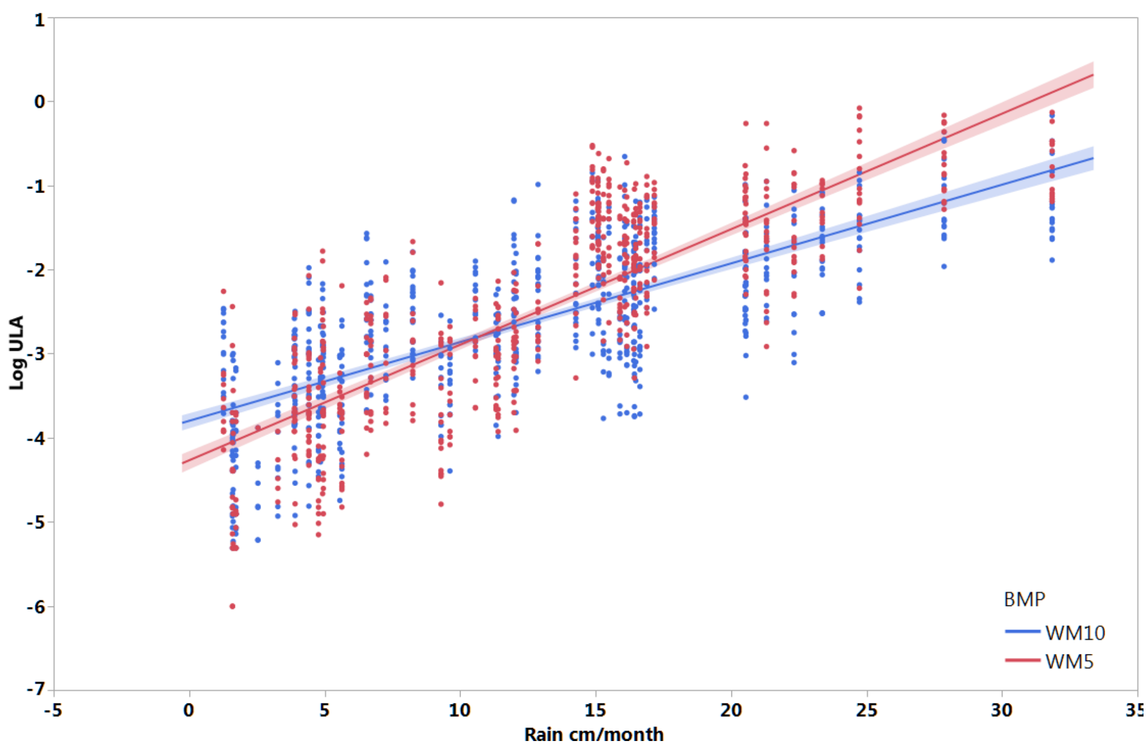


Figure 23- Log ULA vs. rainfall for two groups of farms with BMP type of WM10 or WM5. The linear fits with associated 95% confidence bands are presented.

The best regression models for each year and for all years based on the selected criteria (minimum *AICc*, *VIF*s ≤10 and acceptable plots of residuals) are listed in Table 14. The models were ranked based on their highest adjusted r^2 (Adj r^2) measuring how data match the fitted regression line. The F-test of overall significance was also performed to determine whether these relationships are statistically significant (with the null-hypothesis that the fit of the intercept-only model and our model are equal). If the p-values for the F-test of overall significance are less than the set significance level of $\alpha < 0.05$, the null-hypothesis was rejected, thus indicating that our models provided better fits than the intercept-only models. Table 14 also provides r^2 for the training and validation sets and root mean squared error (*RMSE*) which is the standard deviation of the random error.

Table 14- Best regression models predicting log ULA from environmental explanatory variables in the order of descending r^2Adj.

Year	r^2	r^2Adj	RMSE	r^2 Validation	p-value	Model
2012	0.78	0.77	0.54	0.78	<0.001	$-4.44 + 0.19(\sqrt{MX}) + 0.19R + 0.03AR - 0.02PR + 0.08WM10 + 0.01(R < 13.3) + 0.27(R < 13.3 \times WM10)$
2013	0.76	0.75	0.52	0.78	<0.001	$-3.47 + 0.11(\sqrt{MX}) + 0.05(\sqrt{FA}) + 0.20R - 0.01(DO) - 0.02PR + 0.06WM10 - 0.27(R < 13.3) + 0.25(R < 13.3 \times WM10)$
2010	0.73	0.72	0.57	0.73	<0.001	$-4.20 + 0.11(\sqrt{MX}) + 0.24R + 0.09WM10 - 0.21(R < 13.3) + 0.10(R < 13.3 \times WM10)$
2011	0.71	0.70	0.61	0.67	<0.001	$-5.27 + 0.11(\sqrt{MX}) + 0.42R + 0.04AR - 0.02PR + 0.08WM10 + 0.56(R < 13.3) + 0.24(R < 13.3 \times WM10)$
All Years	0.71	0.701	0.65	0.66	<0.001	$-4.15 + 0.12(\sqrt{MX}) + 0.23R + 0.045AR - 0.01PR + 0.06WM10 + 0.09(R < 13.3) + 0.20(R < 13.3 \times WM10)$
2014	0.68	0.67	0.56	0.66	<0.001	$-4.11 + 0.12(\sqrt{MX}) + 0.22R + 0.03AR - 0.02PR + 0.04WM10 - 0.07(R < 13.3) + 0.21(R < 13.3 \times WM10)$

The statistical measures to judge predictive power of regression models are shown in Table 15. These measures are Bayesian Information Criterion (*BIC*), *AICc* and prediction error sum of squares (*PRESS*). *BIC* is an information-based criterion assessing the model fit (Burnham and Anderson, 2004) and *PRESS* is an estimate of prediction error computed using leave-one-out cross validation (Geladi and Kowalski, 1986). Models with lower statistical measures of *BIC*, *AICc* and *PRESS* are favored. Results indicated that the *BIC*, *AICc* and *PRESS* statistics were the lowest for the year 2012 model and therefore this model had the highest predictive power.

Table 15- AICc, BIC and PRESS statistics of the multiple regression models in the order of ascending PRESS.

Year	*AICc*	*BIC*	*PRESS*
2012	329.09	357.73	75.67
2013	332.26	364.41	79.13
2010	400.00	423.57	98.54
2014	387.36	417.26	107.62
2011	475.72	506.70	122.44
All Years	2001.25	2046.2	503.7

Table 16 through Table 20 present the results of the regression models for years 2010-2014. These tables provide the parameter estimates for each model coefficient, the standard error for each of the estimated parameters (Std Error) and the p-value (α =0.05) for the t-test with the null hypothesis that the true parameter value is zero. They also provide 95% confidence intervals and the *VIF* for each term in the model.

Table 16- Parameter estimates of the regression models for the year 2010.

Term	Estimate	Std Error	p-value	Lower 95%	Upper 95%	*VIF*
Intercept	-4.209	0.140	<0.0001	-4.485	-3.932	-
√MX	0.107	0.016	<0.0001	0.076	0.139	1.180
R	0.243	0.032	<0.0001	0.179	0.307	4.745
WM10	0.092	0.041	0.025	0.012	0.173	1.172
R<13.25	-0.217	0.086	0.012	-0.387	-0.048	4.537
R<13.25*WM10	0.102	0.041	0.013	0.021	0.183	1.196

Table 17- Parameter estimates of the regression models for the year 2011.

Term	Estimate	Std Error	p-value	Lower 95%	Upper 95%	*VIF*
Intercept	-5.270	0.258	<0.0001	-5.778	-4.762	-
√MX	0.106	0.020	<0.0001	0.066	0.146	1.156
R	0.419	0.039	<0.0001	0.341	0.497	9.096
AR	0.110	0.021	<0.0001	0.067	0.153	2.693
PR	-0.016	0.005	<0.0001	-0.025	-0.007	1.286
WM10	0.086	0.045	0.058	-0.003	0.176	1.323
R<13.25	0.559	0.143	<0.0001	0.277	0.842	13.179
R<13.25*WM10	0.238	0.040	<0.0001	0.158	0.317	1.083

Table 18- Parameter estimates of the regression models for the year 2012.

Term	Estimate	Std Error	p-value	Lower 95%	Upper 95%	*VIF*
Intercept	-4.443	0.145	<0.0001	-4.729	-4.157	-
√MX	0.197	0.022	<0.0001	0.154	0.240	1.101
R	0.197	0.017	<0.0001	0.163	0.231	2.157
AR	0.086	0.015	<0.0001	0.056	0.117	1.780
PR	-0.016	0.005	0.001	-0.025	-0.006	1.504
WM10	0.079	0.048	0.100	-0.015	0.174	1.554
R<13.25	0.008	0.061	0.894	-0.113	0.129	2.519
R<13.25*WM10	0.274	0.039	<0.0001	0.197	0.351	1.027

Table 19- Parameter estimates of the regression models for the year 2013.

Term	Estimate	Std Error	p-value	Lower 95%	Upper 95%	*VIF*
Intercept	-3.478	0.185	<0.0001	-3.843	-3.112	-
√MX	0.115	0.023	<0.0001	0.069	0.160	1.381
√FA	0.050	0.023	0.035	0.003	0.096	1.380
R	0.203	0.021	<0.0001	0.161	0.244	3.086
DO	-0.014	0.006	0.025	-0.026	-0.002	1.265
PR	-0.016	0.005	0.002	-0.026	-0.006	1.667
WM10	0.063	0.054	0.246	-0.044	0.171	2.205
R<13.25	-0.273	0.065	<0.0001	-0.402	-0.144	3.109
R<13.25*WM10	0.250	0.037	<0.0001	0.177	0.323	1.029

Table 20- Parameter estimates of the regression models for the year 2014.

Term	Estimate	Std Error	Prob>|t|	Lower 95%	Upper 95%	*VIF*
Intercept	-4.116	0.263	<0.0001	-4.634	-3.597	-
√MX	0.118	0.018	<0.0001	0.082	0.153	1.034
R	0.220	0.038	<0.0001	0.145	0.296	6.898
AR	0.029	0.008	<0.0001	0.014	0.044	1.968
PR	-0.016	0.005	0.001	-0.025	-0.007	1.466
WM10	0.037	0.045	0.419	-0.053	0.126	1.484
R<13.25	-0.068	0.114	0.551	-0.292	0.156	9.205
R<13.25*WM10	0.207	0.038	<0.0001	0.132	0.282	1.030

Figure 24 presents the regression diagnostic plots. The actual vs. predicted plots show the observed values of log ULA against the predicted values of log ULA which is the leverage plot for the whole model (Figure 24A, Figure 24C, Figure 24E and Figure 24G). The points in the actual vs predicted plots are approximately symmetrically distributed around the diagonal line. The residual plotted against the predicted values of log ULA were shown indicating no systematic patterns or evidence of residuals that grow larger as a function of the predicted values (Figure 24B, Figure 24D, Figure 24F and Figure 24H).

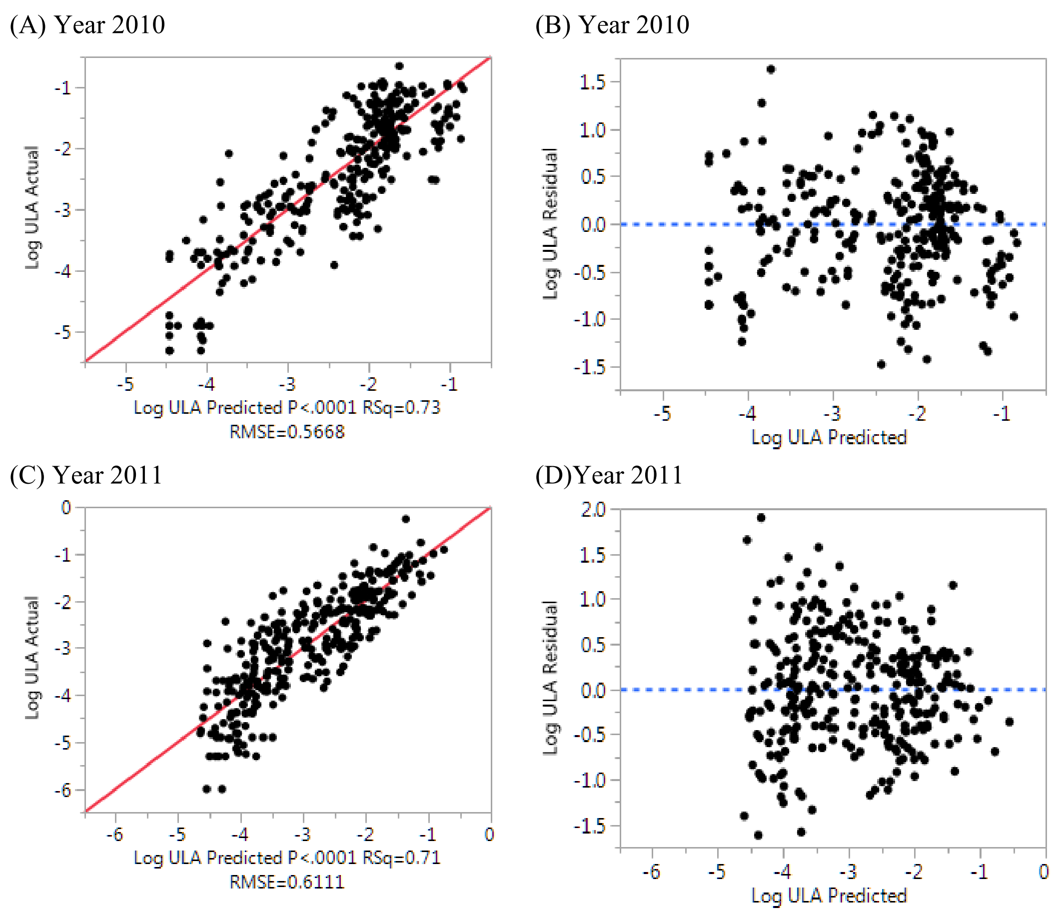


Figure 24- Plots of actual log ULA vs. predicted log ULA (on the left) and plots of residual vs. predicted log ULA (on the right).

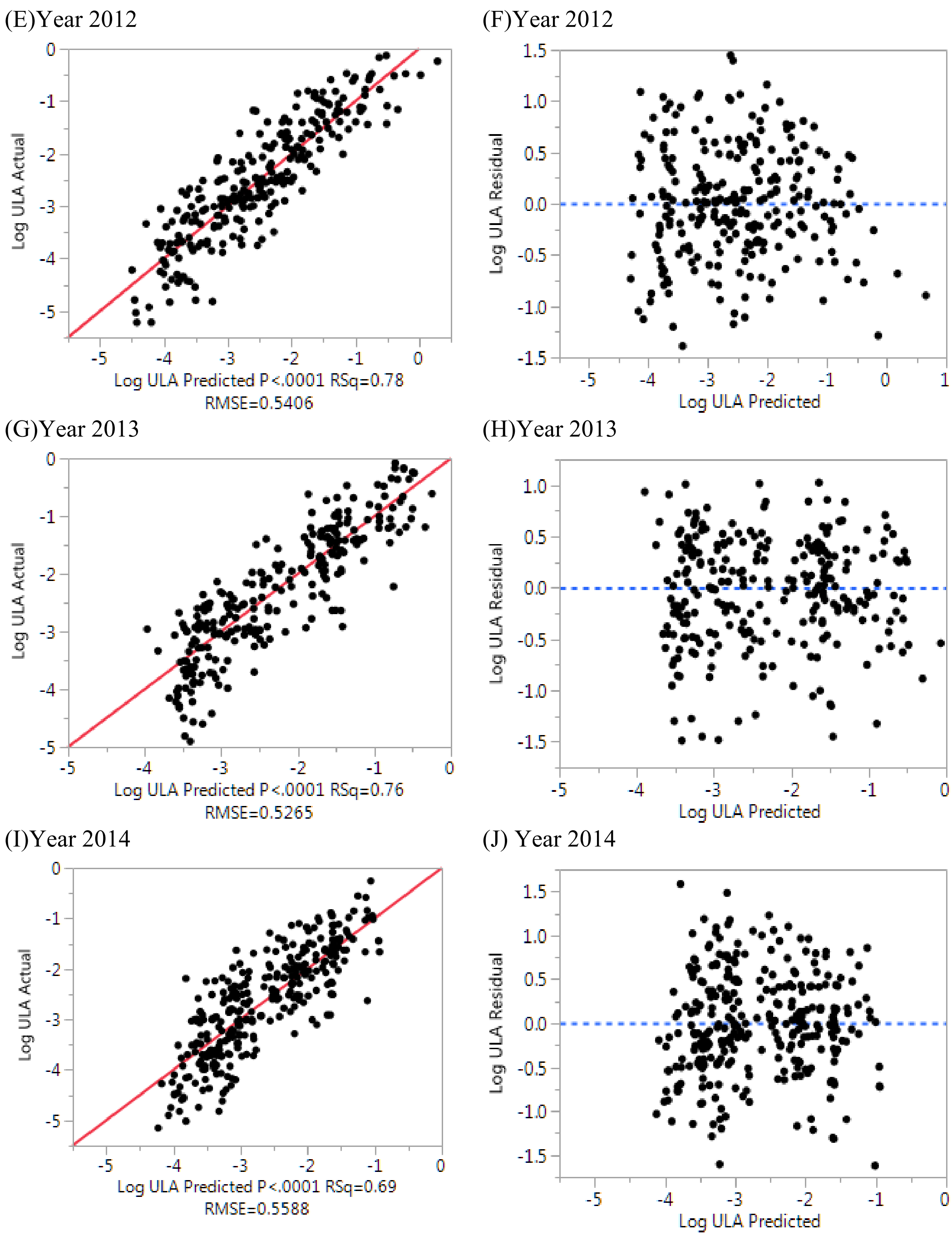


Figure 24- Continued.

Regression models predicting monthly log ULA exhibited approximately similar patterns over the 5 years and also combining all the years together. The model for the year

2011 and all years together showed exact same pattern and therefore I did not discuss the latter separately.

Variables removed due to collinearity included the sugarcane land use to only include the mixed vegetation in the present analysis. The urban land use was not a significant predictor of log ULA and the fallow land use only showed-up in the regression model for the year 2013 (Table 14). The mixed vegetation showed significant role in the regression models. The proportion of the farm with mixed vegetation explained the observed variation in log ULA most consistently across the years and it was a significant predictor of residual variation. The rainfall and the interaction or polynomial effect of the BMP with the rainfall threshold were also important predictors. This highlights the importance of considering the connection between the seasonal changes and BMP types on the log ULA. The individual terms of WM10 in and rainfall threshold (R<13.25) showed some levels of insignificance (Table 16 through Table 20). Even though these individual parameters were not significant, we retained them because the interaction of these two categorical variables is a significant higher-order parameter and the principle of strong heredity states that the model involving a higher-order interaction effect must include all its lower-order components (Chipman, 1996).

The intercepts of the multiple regression models cannot be meaningfully interpreted because assuming all the predictor variables to be zero is not reasonable in this case. So the intercept may only anchor the regression line in the right place or it can be an indication of the value of y-axis variable that is not accounted for by the variables included in the model. The coefficients of continuous and categorical predictor variables can be interpreted implicitly.

Figure 25A through Figure 25D show the changes in regression coefficients of rainfall (R), mixed vegetation (MX), the interaction between the BMP and rainfall threshold (R<13.25*WM10) and the antecedent rainfall (AR) accordingly.

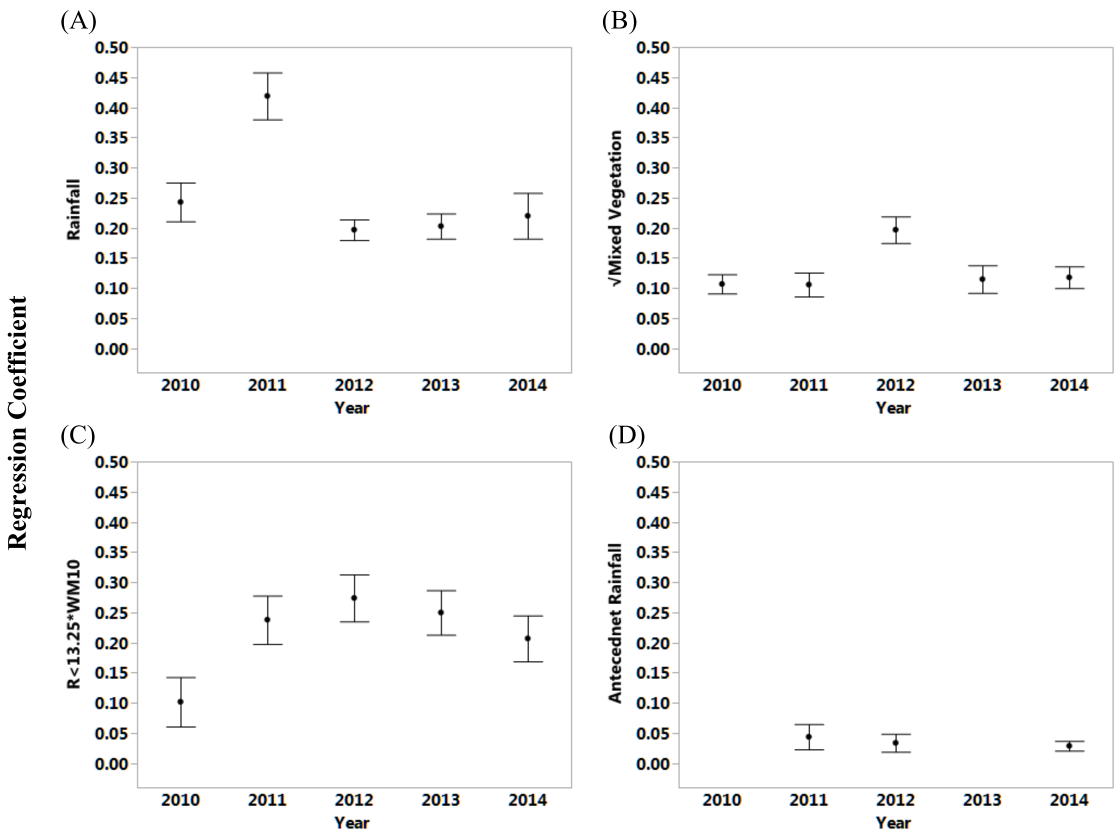


Figure 25- Changes in the regression coefficients for rainfall (A), mixed vegetation (B), interaction between BMP type and rainfall threshold (C) and antecedent rainfall (D).

The regression coefficients for the term perimeter (PR) were constant for all models (-0.016). In multiple regression models, each coefficient is influenced by the other variables and predictor variables are nearly always associated where two or more variables may explain the same variation in the response variable (Cohen et al., 2013). Rainfall coefficient represents the difference in the predicted value of log ULA for each one unit difference in rainfall, assuming all other variables remain constant while considering the model uncertainty and measurement errors. The regression coefficient of the rainfall ranged from +0.20 to +0.42. This suggests that on average, if all variables in the multiple regression model remain constant, one unit change in rainfall will defer log ULA by +0.20 to +0.42 unit with respect to the associated uncertainties. The same interpretation can be used for other continues variables. As might be expected, the antecedent rainfall with coefficients ranging from +0.03 to +0.04 did not have the same strong effect on log ULA as rainfall but still its effect was significant. Daroub et al. (2011) reported the same effect of rainfall and antecedent rainfall on the ULA. On average, a one unit change in square root of mixed vegetation changed log ULA by +0.11 to +0.20 unit if all other variables remained constant. This suggests that the % of land use with mixed vegetation has a significant effect on log ULA comparable to the rainfall effect. The square root of fallow was a significant term in the regression model for year 2013 with a coefficient of +0.05 and % cover of urban and sugarcane were not significant terms in any regression models indicating that the change in log ULA was driven more by % cover of mixed vegetation than by % cover of fallow, sugarcane or urban . The difference in P fertilization average application rates for mixed crop (222 kg P ha^{-1} yr^{-1}) and sugarcane (15.5 kg P ha^{-1} yr^{-1})

could explain this result (SFWMD, 2010). Also studies of tillage effects on P losses showed that tillage increased TP concentration and loads due to increased sediment loss (Bundy et al., 2001). Fields with mixed vegetation land use were tilled prior to planting vegetables while fields with sugarcane land use had no tillage because sugarcane were planted directly into crop residues from previous crop. This can be another reason why % cover of mixed vegetation tended to increase TP loads in runoff.

Likewise, the coefficient of perimeter (-0.016) suggested a negative relation to log ULA. The distant to the outlet term (DO) appeared in the regression model for year 2013 (Table 14) with a regression coefficient of -0.01 with a statistically significant effect on the log ULA. This means that on average, farms that are closer to the sub-basin outlet released more P load than farms further away, assuming other variables constant. Environmental interactions of farms with each other should be investigated to explain the impact of a farm location on water quality (irrigation and runoff).

Regarding the interaction effect of the categorical variables BMP and rainfall threshold, a one unit difference represents switching from one category to another because a categorical variable is coded as 0 or 1. The objective is to define the effect on log ULA between the category for which BMP=WM10 (the reference group) and the category for which BMP=WM5 (the comparison group). Examining Figure 23 and the p-values of the BMP type in the regression models (Table 16 through Table 20), it is apparent that there is a lack of clear differentiation among BMP types, however, BMP type interaction with rainfall threshold had a great predictive strength. The rainfall threshold here is acting as a moderator variable because the effect of BMP type on log ULA differed depending on its value. The regression coefficients of the interaction term ranged from +0.10 to +0.27 with a mean value of +0.21. For two farms with BMP type of WM10, a farm experiencing rainfall >13.25 cm/month would be expected to perform better in terms of controlling P loads in farm runoff than a farm experiencing rainfall <13.25 cm/month. As such, a farm with BMP type of WM5 would be expected to retain P during rainfall <13.25 cm/month. The WM10 strategy delays pumping drainage water based on rain gage measurements and allows detention of 25.4 mm of water with less measures for reducing the movement of particulate matter and sediments (Rice et al., 2002). P release in surface runoff generally occurs in the forms of dissolved or sediment bound P (Sharpley et al., 2000). Erosive soils carry more sediments and are dominated by suspended particulate P (Sharpley et al., 2000). During the peak rainfall months, both dissolved and particulate P concentration increase (Izuno et al., 1991). Particulate matter and sediments control measures are more efficient at reducing particulate P rather than dissolved P during low intensity rainfall. The results from this investigation indicate that during high volume, high intensity rains, water management practices can reduce P load (particulate and dissolved P) more effectively. The relative contribution to the P loads varied considerably between dry and wet seasons and P load was found to be significant during wet season. BMP type of WM10 tended to reduce P loads during wet seasons. Therefore, designing management practices for wet and dry seasons to minimize P load have a major influence on P losses in farm runoff that can overshadow the effects of rainfall alone.

Please note that each coefficient is influenced by the other variables in the regression models and therefore each coefficient does not explain the total effect on log

ULA. Each coefficient represents the additional effect of that variable to the model with the effects of all other variables in the model already accounted for. Adding the interaction term to the model didn't allow the interpretation of the unique effect of BMP type on the log ULA.

4.4 Conclusion

Past research examining environmental and management factors controlling P load in farm runoff in the EAA focused mainly on a limited number of experimental research farms and spatial replication. The present study indicated that by incorporating large scale temporal and spatial dynamics into the study area provided more insight into the factors influencing drainage-water P load. The statistical power of the analysis with a large sample size has benefited largely from adoption of remotely sensed data. Adding the land use information from remote sensing greatly expanded our understanding of the relationships among the environmental and management variables impacting the amount of P load in farm runoff. Both rainfall and antecedent rainfall were important factors in explaining the variation of log ULA. Difference in log ULA among farms was largely attributed to the % cover of mixed vegetation and BMP type. The proposed model relating P load in terms of log ULA to environmental and management factors including rainfall, antecedent rainfall, land use, farms size, location of the farm, seasonality and BMP type can be used for particular prediction necessary for farm management.

The study indicated that the greatest potential for reducing P load in farm runoff lies in developing and implementing more rigorous BMPs in the study area. Both BMP strategies of WM10 and WM5 had equivalent assigned points according to the SFWMD.

Runoff amounts were much higher during wet seasons and BMP WM10 retained more water compared to BMP WM5, resulting in a better control of P loading during storm events. BMP WM5, having more measures of particulate matter and sediment controls enhanced the control of P loading off the farm during rainfall events of less than 13.25 cm/month. An effective BMP must control P load off farms during all rainfall conditions thus we recommend adopting at least a combination of BMP WM10 and WM5 strategies is necessary to successfully prevent P from entering the sensitive Everglades wetlands. This study shows that the relationship between P loss in farm runoff and rainfall can be masked if appropriate management practices designed for wet and dry season are applied.

5. CONCLUSIONS

Water and P budgets in the EAA sub-basin and canals were developed from water years 2005 through 2012 to identify the main source of P in the EAA and to estimate the amount of P load retained in the EAA soils and canals. Phosphorous load from the surface inflow and atmospheric deposition represented 15% and 10% of the total P load into the EAA, respectively, while the net P import contributed about 75%. The EAA soil is retaining a P load of approximately 412 mtons yr^{-1} which is an indicator soil P accumulation or immobilization leading to the build-up of legacy P. P load from surface inflows and from farm drainage contributed 34% and 66% of the total P load to the canals, respectively. The canals within the EAA assimilated the total P load of 64.8 ± 9.6 mtons yr^{-1} of the total P load. Results showed that the canal attenuation would reduce the impact of farm P loadings on the basin outlet and confirmed the function of canal P assimilation in reducing the impact of farm P loadings on the total outflow P loadings. Dimensionless impact factors (I_1 and I_2) were developed and used to assess the degree of impact of the farms P loadings onto the Everglades wetlands.

Remote sensing has facilitated advances in the modeling and understanding of environmental sciences. A novel approach to discriminate sugarcane from other crops using time series of satellite images integrating information from crop growth cycle was developed. We successfully discriminated sugarcane from mixed vegetation, fallow and urban area in the S5A sub-basin of the EAA with the overall accuracy of 94% for the five consecutive years from 2010 to 2014. The wealth of information obtained from remote sensing enabled us to perform the large scale multivariate analysis to identify factors affecting P loadings in the S5A sub-basin with existing BMPs. The study indicated that while rainfall is the major driving force of P load in the farm runoff, implementing more rigorous BMPs with respect to the seasonality and rainfall intensity has the potential for reducing P load in farm runoff. Also the percentage of mixed vegetation land-use significantly impact P. Results from this work showing that environmental and management practices have significant effects on P loads in farm runoff , emphasize the need to design management practices for wet and dry seasons. The findings presented herein is not unique to the EAA and can be applied to the similar agricultural areas. The EAA represents one of the largest agricultural areas and P load has been extensively measured in this area and therefore may be the best to understand and address the practices that can help reduce P loads in farm runoff.

In the course of this research, we identified some areas where future research was needed. The areas of further research include the following:

Characterizing different forms of P (particulate and soluble forms of P) in the EAA with focus on better characterization of quantity and quality of sources of P and transport mechanism in the EAA canals. Also an extensive biogeochemistry analysis on the P contents of sediments, suspended solids and biotic growth in the EAA primary canals is recommended.

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